

AI-Based Recruitment Systems and Language Bias: Implications for Human Resource Management and Applied Linguistics

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Abstract - The modern advancements in artificial intelligence (AI) technology have led to a shift in human resource management due to processes such as automated hiring of candidates, semantic matching, and evidence-based decision-making. In turn, their dependence on linguistic information triggers certain concerns about language biases, algorithmic fairness, transparency, and diversity in recruiting. The present research is dedicated to the perspectives of AI recruiting and the connection between concepts such as language bias, applied linguistics, algorithmic fairness, transparency, candidate trust, and diversity in HRM. The methodological framework is based on the application of quantitative research and the collection of information via an online survey with 15 research statements (five-point Likert scale) and six sample characteristics from 213 participants. Descriptive statistics, reliability analysis, the Spearman-Brown procedure for two-item constructs, and Pearson correlation analysis will be used. The results have indicated a relatively positive attitude towards AI-based recruiting, with Inclusive HRM showing the highest construct mean ($M = 4.01$), followed by Transparency and Candidate Trust ($M = 3.93$). Language bias demonstrated high internal consistency ($\alpha = 0.85$), while AI recruitment yielded $\alpha = 0.78$. The two-item constructs evaluated via the Spearman-Brown procedure demonstrated robust reliability, with Inclusive HRM achieving $r_{sb} = 0.81$, Applied Linguistics $r_{sb} = 0.79$, and Algorithmic Fairness $r_{sb} = 0.71$. The strongest correlation ($r = 0.479$) was identified between algorithmic fairness and transparency, highlighting the necessity to pay attention to both. The results prove the significance of language diversity considerations, algorithmic transparency, fairness assessment, candidate trust, and human control for developing an inclusive recruiting process with the help of AI.

Keywords: Artificial Intelligence Recruitment, Language Bias, Applied Linguistics, Algorithmic Fairness, Inclusive HRM, Candidate Trust

I. INTRODUCTION

The introduction of artificial intelligence (AI) into human resource management (HRM) has been increasingly used for sourcing candidates, screening their resumes, matching the requirements to qualifications, assessments, and decisions of recruitment (Johnson et al., 2022). Various techniques of

machine learning and natural language processing (NLP) help recruitment systems to handle big data about the candidates and identify similarities between the requirements of a certain position and the profiles of applicants. For instance, AI-based recruitment systems utilize such techniques as latent semantic analysis (LSA), Bidirectional Encoder Representations from Transformers (BERT), and support vector machines (SVM) (Tian et al., 2023). There is a wide range of current research on how AI is being integrated into HRM and what benefits it can provide (Iancu & Oprea, 2025; Alshahrani et al., 2025; Venugopal et al., 2024).

However, while bringing various benefits to recruitment and decision-making in HRM, the growing use of algorithms in recruitment also poses the problems of algorithmic fairness and language bias. The recruitment system handles plenty of linguistic data such as resumes, cover letters, written answers to questions, transcriptions of interviews, job descriptions, etc. Hence, linguistic features can affect automated evaluation although they are not related to job performance itself. The risks of discrimination due to AI-based HRM have already been detected in the literature. Moreover, current research proves that the language that is generated or interpreted by an AI system reproduces gender bias (Sivakaminathan & Musi, 2026; Sony et al., 2025). This issue becomes especially important in cases of multilingual workplaces.

It is relevant from the perspective of applied linguistics since the process of recruitment implies linguistic representation and assessment. AI systems may implicitly favor certain linguistic norms, whereas they treat other language variations unfavorably. Cross-linguistic studies have shown that the AI-generated language may replicate gender-based biases in different languages, which shows that linguistic variety should be considered when studying bias in AI decision-making (Voutyrakou & Skordoulis, 2025). Likewise, AI-assisted recruitment calls for recognizing ethical risks of automated recruitment and keeping proper human control (Hunkenschroer & Luetge, 2022; Sýkorová et al., 2024).

Recently, the literature on HRM became increasingly focused not only on whether AI could contribute to increased efficiency in recruiting but also on how to identify, evaluate, and manage the biases (Pandey et al., 2025). In this way, there is an approach to minimizing the bias of AI systems in the processes of recruitment and selection by focusing on organizational and context-specific measures for bias management (Soleimani et al., 2025). In this regard, reviews of AI techniques for algorithmic bias in hiring point out the relevance of the fair design and evaluation of these algorithms (Albaroudi et al., 2024). Furthermore, human-centered approaches to AI recruitment stress the importance of integrating technology and human decision-making as well (Peña et al., 2023). Recent research links AI adoption with broader diversity, equity, and inclusion (DEI) considerations within HRM (Naoum et al., 2026).

Nevertheless, the interaction between language bias, AI recruiting, the HRM decision-making process, and applied linguistics has not been adequately studied from the user side. Previous studies have considered the issue of algorithmic discrimination, gender and racial differences, ethical use of AI, and efficiency of recruitment, but not enough attention has been paid to linguistic diversity and language bias in AI-assisted recruiting (Sivakaminathan & Musi, 2026; Sony et al., 2025; Gaebler et al., 2024). In particular, this is crucial for employment settings with linguistic and cultural diversity.

Thus, this research deals with language bias perception in AI recruitment systems and its implications for HRM and applied linguistics. The current study considers the following research questions:

RQ1: How is the adoption of AI-based recruitment systems perceived in relation to recruitment efficiency?

RQ2: To what extent is language bias perceived in AI-assisted recruitment?

RQ3: How does perceived language bias relate to perceptions of algorithmic fairness?

RQ4: What are the implications of linguistic diversity for AI-based recruitment and inclusive HRM?

Objectives of the Study

1. To examine the perceptions of AI-based recruitment systems among respondents.
2. To investigate the perceived presence and influence of language bias in AI-assisted recruitment.
3. To evaluate respondents' perceptions of algorithmic fairness in AI-based recruitment systems.
4. To assess the perceived transparency of AI-based recruitment processes.
5. To examine the implications of linguistic diversity for inclusive Human Resource Management (HRM) practices.

The importance of this study lies in the fact that it bridges the AI-based recruitment with applied linguistics while moving away from usual demographic traits when discussing recruitment bias. Moreover, empirical evidence in this case is provided by the answers of 213 respondents who filled in a 15-question structured questionnaire. The results obtained during this study are believed to be beneficial for HR managers, AI experts, and businesses in general when creating more transparent and linguistically diverse recruitment procedures.

In this research paper, right after the introduction, Section 2 (literature review) provides all background information regarding the topic. Then, in Section 3, the methodology of the research (research design, questionnaire development, data collection, measurement of constructs, and statistical analysis) is provided; Section 4 describes the research framework and hypotheses; in Section 5, the results and analysis (descriptive statistics, reliability analysis, correlation analysis, and hypotheses testing) are presented; finally, in Section 6, there is the discussion of results, implications, limitations, and further research directions. Finally, Section 7 concludes this research paper with the summary of key contributions and implications of AI-based recruitment for HRM.

II. LITERATURE REVIEW

2.1 AI-Based Recruitment and Human Resource Management

The use of AI in human resource management has brought transformation to the process of recruitment by automating the processes of candidate selection, resume analysis, job matching, and decision-making. Systems for recruitment have become capable of processing large amounts of data about candidates owing to the use of NLP and machine learning techniques to identify the relationship between the profile of the candidates and the job description (Tian et al., 2023; Ajjam & Al-Raweshidy, 2025). Moreover, there have been recent studies that show the benefits of AI in the improvement of the efficiency of the process of recruitment, workforce planning, and scaling of HR (Iancu & Oprea, 2025; Venugopal et al., 2024). However, dependency on recruitment systems has created concerns related to transparency, accountability, and human control (Hunkenschroer & Luetge, 2022; Sýkorová et al., 2024).

In light of this, it is important to realize that the application of AI recruitment technology should be seen as a tool to assist the decision-making process and not a substitution of humans' decision-making (Horodyski, 2023). Specifically, according to the results of the research carried out to explore the views of recruiters on this issue, acceptance of AI was determined by their awareness of the capabilities and limitations of AI (Horodyski, 2023). Furthermore, recent research revealed that the successful application of AI technology for the purposes of recruitment required collaboration between HR specialists and the developers of AI technology to overcome decision-making biases

(Soleimani et al., 2025). These findings establish the importance of examining not only the technological performance of recruitment systems but also how their outputs are interpreted within HRM.

2.2 Algorithmic Bias in AI Recruitment

Algorithmic bias is one of the major concerns of AI recruiting. The algorithmic recruiting systems are based on the dataset, which might include past discriminations and inequalities in organizations and society (Sony et al., 2025; Albaroudi et al., 2024). This means that such algorithms will reproduce and amplify the existing inequalities instead of resolving them. Furthermore, interdisciplinary research on the issue of algorithmic recruiting demonstrates that fairness is a multifaceted concept that includes datasets, algorithms, evaluation metrics, organizational approach, and governance frameworks. Hence, modern research is aimed at identifying approaches to understanding and reducing the bias in AI systems. To reduce the bias, it is crucial to take into account the whole process of recruiting ecosystem: the training datasets, the algorithm itself, the human decision-making process, and the organizational environment (Soleimani et al., 2025; Albaroudi et al., 2024). Moreover, ethical recruiting research highlights the importance of such concepts as fairness, transparency, accountability, and appropriate human involvement (Hunkenschroer & Luetge, 2022; Sýkorová et al., 2024). Thus, it can be concluded that the AI recruitment can be evaluated not only in terms of efficiency but also equity.

2.3 Language and Linguistic Bias in AI Recruitment

The linguistic dimensions assume importance in the context of recruitment using AI because many recruitment decisions are made based on information provided in language. Resumes, cover letters, job descriptions, tests, chatbot answers, and interview records can all be analyzed through NLP techniques. This means that linguistic dimensions could become features of the information used to analyze recruitment (Tian et al., 2023; Ajjam & Al-Raweshidy, 2025).

Some evidence indicates that the language can cause bias in the recruitment process through AI. It was demonstrated in research conducted about recruitment using ChatGPT that gender-specific characteristics of the job description would be present in the resume screening, indicating that AI can recreate the linguistic patterns present in recruitment information (Sivakaminathan & Musi, 2026). The implications of the finding for applied linguistics are significant because language is not just an input for the recruitment algorithm, but certain linguistic choices can influence its automated evaluation.

Moreover, cross-linguistic studies have demonstrated that AI-generated language may reproduce gender patterns in various languages (Voutyrakou & Skordoulis, 2025). Thus, linguistic and cultural differences should be considered when discussing the fairness of AI. In multilingual recruitment processes, candidates can differ in vocabulary, grammatical

structure, dialects, accent, style of writing, or preferred language despite having identical professional competencies. In case when recruitment algorithms associate certain linguistic patterns with desirable traits of candidates, such a practice can lead to discrimination.

2.4 AI, Applied Linguistics, and Recruitment Fairness

Whereas the convergence between AI in recruiting and applied linguistics is less explored in comparison to the study of algorithmic discrimination in general terms, the existing literature on recruiting has mostly addressed demographic discrimination, model fairness, bias in training data, and governance in AI (Sony et al., 2025; Albaroudi et al., 2024; Hunkenschroer & Luetge, 2022). The process by which information about candidates is represented and evaluated linguistically, however, requires further exploration.

Language-based AI systems can learn correlations using large datasets, and thus, social stereotypes and biased linguistic representation can be incorporated in automated systems (Sivakaminathan & Musi, 2026). Similarly, recent research on large language models and recruiting proves that demographic information can influence model performance, and bias reduction must be incorporated in the learning process. As such, applied linguistics represents a useful viewpoint in examining how linguistic decision-making and linguistic variation can shape the outcome of AI recruitment processes.

This perspective is especially pertinent to inclusive HRM because linguistic diversity is not necessarily linked to lack of competence, professionalism, and suitability for a job position. Recruiting systems must differentiate between job-related communication demands and language features that are simply characteristic of an individual's linguistic or cultural background. This way, the system will avoid being discriminatory in favor of linguistic norms.

2.5 Human Oversight, Transparency, and Inclusive HRM

Human oversight becomes increasingly recognized as an essential element for protection against misuse of AI systems in job search procedures. The human-centered perspective assumes that the automated system must assist but not replace the professional judgment (Peña et al., 2023). Responsible research on conversation AI and HR technologies points out the necessity for responsible human interference when it comes to employment decisions made by AI systems (Andreas, 2024).

Transparency is also vital since both candidates and HR experts can lack knowledge regarding how AI systems process language and produce the recommendations concerning recruitment. Transparency is vital for building trust and preventing discrimination since it is challenging to identify any discriminative actions otherwise. Recent research on AI recruitment stresses the importance of organizational learning, discrimination identification, and correction instead of treating fairness as a technical measure

once and forever (Gia Hoang et al., 2026). The connection between AI and diversity, equity, and inclusion becomes an intricate matter since AI provides standardized evaluation while replicating existing inequality in data and design (Naoum et al., 2026). Thus, the literature suggests the combination of human-centeredness and inclusiveness, where the efficiency of AI is complemented by continuous control, transparency, awareness of linguistic diversity, and human oversight.

2.6 Research Gap

There are many interests in AI-based recruitment, algorithmic fairness, HRM transformation, and discrimination threats in the literature that is available today. However, the problem of language bias as one of the issues related to AI-assisted recruitment has been studied very poorly and has not gotten enough empirical attention so far. There have been identified some gendered language and demographic biases in AI-based systems; however, it is necessary to conduct more empirical research to clarify the way people perceive linguistic bias, algorithmic fairness, transparency, and diversity of language in recruitment. In this connection, the current study will attempt to fill this gap by studying people's perception of AI recruitment implementation, language bias, applied linguistics, algorithmic fairness, transparency, candidate trust, and inclusive HRM based on the gathered data of 213 respondents. The contribution of this study to the previous literature will be to consider language as a relevant factor for algorithmic fairness of recruitment.

2.7 Research Hypotheses

- **H1:** Perceptions of AI-based recruitment operate independently of perceptions regarding inclusive HRM practices.
- **H2:** Applied Linguistics awareness exhibits a neutral baseline relationship with inclusive HRM practices in direct linear assessment.
- **H3:** Algorithmic Fairness has a positive relationship with Transparency in AI-based recruitment systems.
- **H4:** Candidate Trust and inclusive HRM practices do not share a direct linear correlation, functioning as independent perceptual constructs.

III. RESEARCH METHODOLOGY

3.1 Research Design

In this study, a quantitative research design was employed to explore the perceptions of AI-enabled recruitment systems and their association with language bias, applied linguistics, algorithmic fairness, transparency, candidate trust, and inclusive human resource management (HRM). A questionnaire-based survey research design was applied for collecting empirical data from the respondents. The quantitative research design was chosen since the main aim of this study is to identify the perception-based variables and their associations. The methodology of this research included questionnaire design, data collection, data preparation, data reliability evaluation, correlation analysis, and interpretation of results. The entire process of research methodology is illustrated in fig. 1.

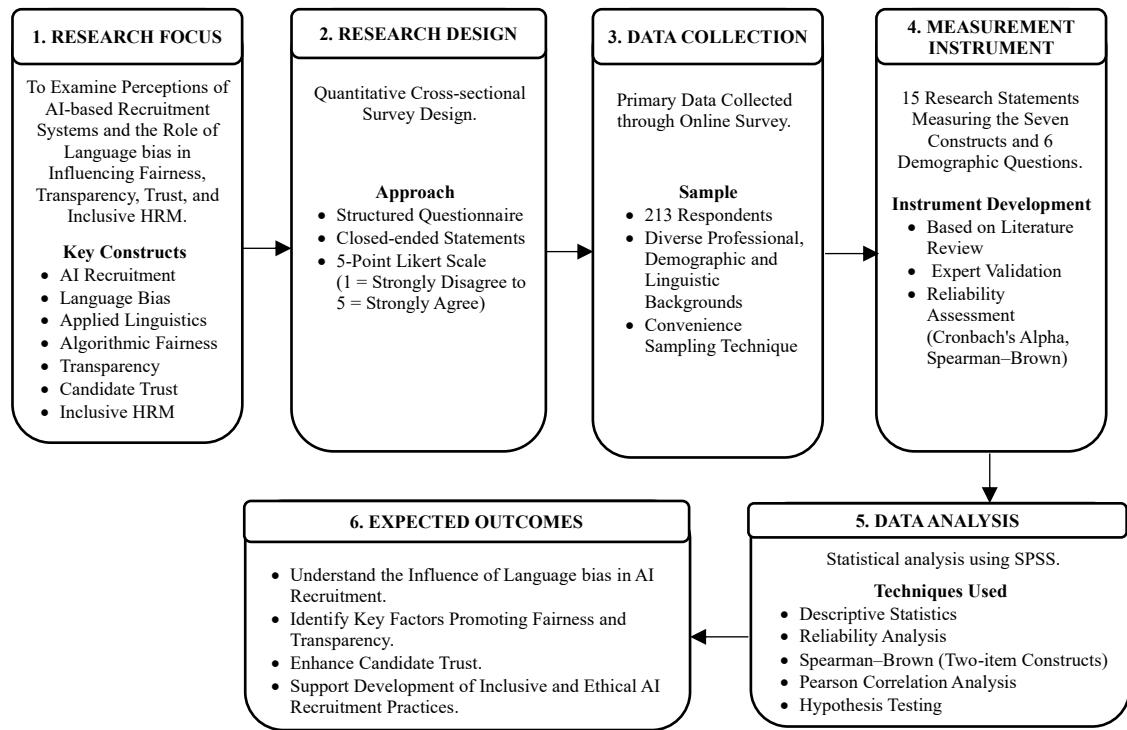


Fig. 1 Research Methodology Framework for Examining AI-Based Recruitment and Language Bias

3.2 Questionnaire Development

A set of structured questions comprising 21 items was formulated with respect to the research objectives and review of literature. The structured survey instrument comprised 21 total items: 6 demographic queries (Columns A1–F1: Age Group, Gender, Industry/Sector, Current Role, Geographic Location, and English Language Background) and 15 core research statements (Columns G1–U1 / Q1–Q15) evaluated on a 5-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). Construct operationalization mapped directly to the items: AI Recruitment (Q1–Q3), Language Bias (Q4–Q7), Applied Linguistics (Q8–Q9), Algorithmic Fairness (Q10–Q11), Transparency (Q12), Candidate Trust (Q13), and Inclusive HRM (Q14–Q15). The complete item text is detailed in Appendix A. The constructs were assessed using the following research items: AI Recruitment, Language Bias, Applied Linguistics, Algorithmic Fairness, Transparency, Candidate Trust, and Inclusive HRM. AI recruitment was measured through Q1–Q3, language bias through Q4–Q7, applied linguistics through Q8–Q9, algorithmic fairness through Q10–Q11, transparency through Q12, candidate trust through Q13, and inclusive HRM through Q14–Q15. The measurement for all the research items involved a five-point Likert scale from 1=Strongly Disagree to 5=Strongly Agree. Sample-characteristic questions pertained to age group, gender, industry/sector, position held, geographical location, and English language background.

3.3 Data Collection and Sample

Data used in the research involved a gathered dataset with 213 participants. Data was gathered using a structured survey sent to individuals who have knowledge or experience concerning recruitment processes, HR operations, office technologies, and AI applications. Responses received from the gathered participants were coded into numbers for statistical calculations, whereby Likert-scale responses were encoded with values between 1 and 5. The sample description has been carried out separately to provide an overview of the diversity of the respondents.

3.4 Measurement Constructs

The measurement framework is based on the conceptual framework that was introduced. AI recruitment is a perception of AI use and effectiveness, and language bias is the perception of any disadvantage that might occur in the language of AI-based recruitment. Applied linguistics deals with recognition of linguistic diversity, and algorithmic fairness is concerned with testing and human supervision of algorithmic processes. Transparency, candidate trust, and inclusive HRM represent perceptions regarding responsible AI implementation and organizational inclusion.

3.5 Data Preparation and Statistical Analysis

A complete analysis of the dataset was done before the analysis in terms of its completeness, consistency, and

coding. Descriptive statistics such as frequency, mean, and standard deviation were employed to characterize respondent and research variables. Reliability testing was done using Cronbach's alpha test when there were more than two items in the construct, while the Spearman-Brown coefficient test was employed when there were only two items. The relationship between AI recruitment, language bias, applied linguistics, algorithmic fairness, transparency, candidate trust, and inclusive HRM was tested using Pearson correlation analysis. The framework tests direct bivariate associations among system factors rather than complex mediation paths. Pearson correlation analysis is utilized to establish linear alignment between operational variables (such as Algorithmic Fairness and Transparency) and outcome perceptions (Inclusive HRM).

3.6 Validity and Reliability

The questionnaire was built using the constructs extracted from the literature on AI recruitment, algorithmic discrimination, linguistic diversity, and ethics in HR practices. Thus, the alignment among the research questions, theoretical framework, and measurement instruments was achieved. Cronbach's alpha (α) was applied to evaluate internal consistency for constructs with more than two items (*AI Recruitment* and *Language Bias*). For the two-item constructs (*Applied Linguistics*, *Algorithmic Fairness*, and *Inclusive HRM*), the Spearman-Brown prophecy formula (r_{sb}) was computed to evaluate split-half reliability, as Cronbach's alpha underrepresents internal consistency when item count $k = 2$. Values of $r_{sb} \geq 0.70$ were established as the benchmark for acceptable construct reliability. Transparency and candidate trust were measured using single-item indicators, so no internal consistency analysis was performed.

3.7 Ethical Considerations

The research complied with the ethics of using questionnaires. The respondent information was handled in a confidential manner and analyzed on an aggregate basis only. The demographic information was used solely to describe the respondents and for research analysis. The collected information was used for academic purposes only.

IV. PROPOSED CONCEPTUAL FRAMEWORK

The conceptual framework illustrates the direct relational structure among the core constructs: independent technological and linguistic factors (AI Recruitment, Language Bias, Applied Linguistics), system operation factors (Algorithmic Fairness, Transparency, Candidate Trust), and organizational outcomes (Inclusive HRM). Rather than positing formal mediation chains, this model evaluates direct associations and operational alignment between candidate perceptions, system attributes, and inclusive practices. This framework is built on the basis of the research gap found in the literature and can serve as a tool to analyze the impact of AI recruitment technologies on the issues of linguistic assessment, fairness perception, and inclusive

HRM. AI recruitment technologies constitute the technological component of the proposed framework. Using AI technologies, which involve automated screening, semantic matching, and NLP-based candidate evaluation, one can enhance the efficiency of the recruitment process and assist HR professionals in dealing with large numbers of applications (Iancu & Oprea, 2025; Tian et al., 2023; Ajjam & Al-Raweshidy, 2025). However, since AI recruitment technologies use information about candidates' linguistic features, their performance may be impacted by linguistic factors, limited availability of training data, and algorithmic biases (Sivakaminathan & Musi, 2026; Sony et al., 2025).

Language bias constitutes the core issue within the proposed framework. Using AI recruitment technologies, one may assess different candidates in a biased way due to vocabulary choices, writing styles, regional language variations, non-standard English language usage, and multilingualism. From the point of view of applied linguistics, the linguistic differences of candidates do not indicate their lack of professionalism; therefore, it is important to identify and resolve language biases in AI recruitment systems (Sivakaminathan & Musi, 2026; Voutyrakou & Skordoulis, 2025).

Applied linguistics is used as the theory to address linguistic diversity in AI-based recruitment. Recognition of the legitimacy of linguistic diversity will help in building recruitment systems that assess candidates' skills and competencies associated with job requirements rather than preferred language styles. This approach is one of the ways through which inclusion promotes inclusion in HRM (Naoum et al., 2026).

Algorithmic fairness and transparency serve as tools for mitigating the risk of any form of bias in AI-based

recruitment. The algorithmic fairness helps in ensuring that AI-based systems evaluate candidates equally, while transparency will allow organisations and candidates to know how the AI-based recruitment decisions are made. Some measures include bias auditing, explainability of AI-based systems, and a human review process (Soleimani et al., 2025; Albaroudi et al., 2024; Hunkenschroer & Luetge, 2022). In addition, human-centric AI approaches focus on helping HR professionals in decision-making rather than taking over their responsibilities (Peña et al., 2023).

Candidate trust is an important result of the framework that is impacted by fairness and transparency perception. Candidates who have positive perceptions of the transparency and fairness of AI-based recruitment systems and recognition of linguistic diversity are more likely to have high acceptance and trust in the AI-assisted recruitment process. However, the presence of language-related bias will lower the level of trust in the automated recruitment process.

Inclusive HRM stands for the organisational result. With responsible development and implementation of AI-based recruitment systems, they may be able to support diversity, equality, and inclusion. Otherwise, the unrecognized linguistic and algorithmic biases will cause inequality and further disadvantage people (Sony et al., 2025; Naoum et al., 2026).

To examine how candidates differentiate system adoption from organizational outcomes, H1, H2, and H4 hypothesize independence (null direct linear effects) between general adoption/awareness variables and perceived HRM inclusiveness. Conversely, H3 posits a positive relationship between operational fairness and transparency.

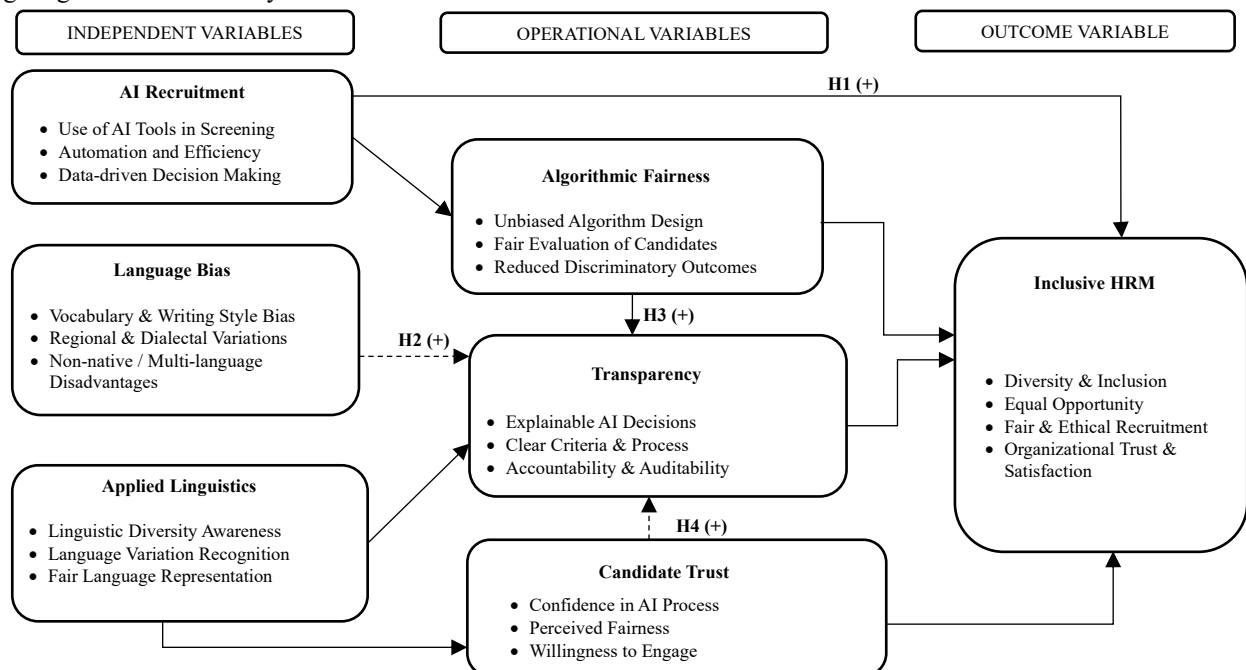


Fig. 2 Proposed Conceptual Framework of AI-Based Recruitment and Language Bias

Fig. 2 shows how the framework suggests that AI-supported recruitment not only enhances the efficiency of the recruiting process but also raises risks of language bias that could occur as a result of implementing AI. Applied linguistics promotes appreciation of linguistic diversity, while algorithmic fairness, transparency, and human supervision are the tools to reduce the bias. They impact candidate trust and lead to inclusive HRM.

The presented framework considers the technological, linguistic, and organizational aspects of AI-supported recruiting and is the theoretical basis for investigating the connections between these phenomena in this study.

V. RESULTS AND ANALYSIS

5.1 Sample Characteristics Analysis

The analysis focused on the responses collected from 213 participants. Demographic characteristics of the sample include age group, gender, industry, position, geographical location, and prior exposure to the English language. The demographic characteristics give an overview of the diverse pool of participants in the study.

TABLE I SAMPLE CHARACTERISTICS OF RESPONDENTS (N = 213)

Demographic Characteristic	Category	Frequency (n)	Percentage (%)
Age Group	18–25	48	22.54%
	26–35	78	36.62%
	36–45	42	19.72%
	46–55	26	12.21%
	56+	19	8.92%
Gender	Male	105	49.30%
	Female	104	48.83%
	Other	4	1.88%
Industry/Sector	Information Technology & Services	72	33.80%
	Human Resources & Recruiting	54	25.35%
	Corporate & Business Services	41	19.25%
	Education & Academia	28	13.15%
	Other Sectors	18	8.45%
Position Held	Entry-Level / Junior Specialist	61	28.64%
	Mid-Level Specialist / Analyst	84	39.44%
	HR Manager / Recruiting Lead	45	21.13%
	Senior Management / Executive	23	10.79%
Geographical Location	North America	68	31.92%
	Europe	74	34.74%
	Asia-Pacific	51	23.94%
	Rest of World	20	9.39%
English Language Background	Native English Speaker	82	38.50%
	Fluent / Non-Native Professional	96	45.07%
	Intermediate / Multilingual User	35	16.43%

The results presented in table I reveal that the greatest share of participants was comprised of those aged 26–35 (36.62%) and those aged 18–25 (22.54%). The gender ratio was quite similar, with an approximately equal number of male and female participants. Different occupational positions and language backgrounds of the participants made it possible to examine the perception of artificial intelligence recruitment under various conditions.

5.2 Descriptive Analysis

The experiment was conducted using fifteen research statements related to AI recruitment, language bias, applied linguistics, algorithmic fairness, transparency, candidate trust, and inclusive HRM. All statements were analyzed using a five-point Likert scale, which ranges between 1 (Strongly Disagree) and 5 (Strongly Agree). The results are provided in table II below.

TABLE II DESCRIPTIVE STATISTICS OF RESEARCH ITEMS (N = 213)

Item	Mean	SD
Q1	3.71	0.74
Q2	3.73	0.78
Q3	3.73	0.76
Q4	3.51	0.76
Q5	3.54	0.83
Q6	3.36	0.79
Q7	3.49	0.76
Q8	3.79	0.79
Q9	3.89	0.74
Q10	3.82	0.77
Q11	3.88	0.77
Q12	3.93	0.81
Q13	3.93	0.77
Q14	3.98	0.71
Q15	4.04	0.74

As depicted in table II, all research questions have mean scores higher than the neutral midpoint (3.00), which reflects the positive attitude towards the AI-based recruiting process and inclusion of human resources. The highest mean score was found for the question Q15 ($M = 4.04$, $SD = 0.74$), which implies the strong agreement of the respondents about AI recruiting as a tool for providing the equal evaluation of candidates with diverse linguistic and cultural background. The next highest mean score was found for Q14 ($M = 3.98$, $SD = 0.71$), which reflects the strong agreement of the respondents about the reduction of the language barrier as an instrument of diversity promotion in the workplace. The relatively lowest mean score was found for Q6 ($M = 3.36$, $SD = 0.79$).

5.3 Construct-Level Analysis

These 15 research statements were classified under seven constructs based on the suggested theoretical framework. The construct level results are shown in table III.

TABLE III CONSTRUCT-LEVEL DESCRIPTIVE STATISTICS

Construct	Items	Mean	SD
AI Recruitment	Q1–Q3	3.72	0.43
Language Bias	Q4–Q7	3.47	0.40
Applied Linguistics	Q8–Q9	3.84	0.52
Algorithmic Fairness	Q10–Q11	3.85	0.54
Transparency	Q12	3.93	0.81
Candidate Trust	Q13	3.93	0.77
Inclusive HRM	Q14–Q15	4.01	0.56

From table III, it is observed that the highest construct mean was obtained from the Inclusive HRM ($M = 4.01$), and the next highest mean was for Candidate Trust and Transparency ($M = 3.93$). It proves that respondents are very much concerned about the fairness, transparency, and inclusiveness of the AI-enabled recruitment process. The lowest construct mean was for language bias ($M = 3.47$).

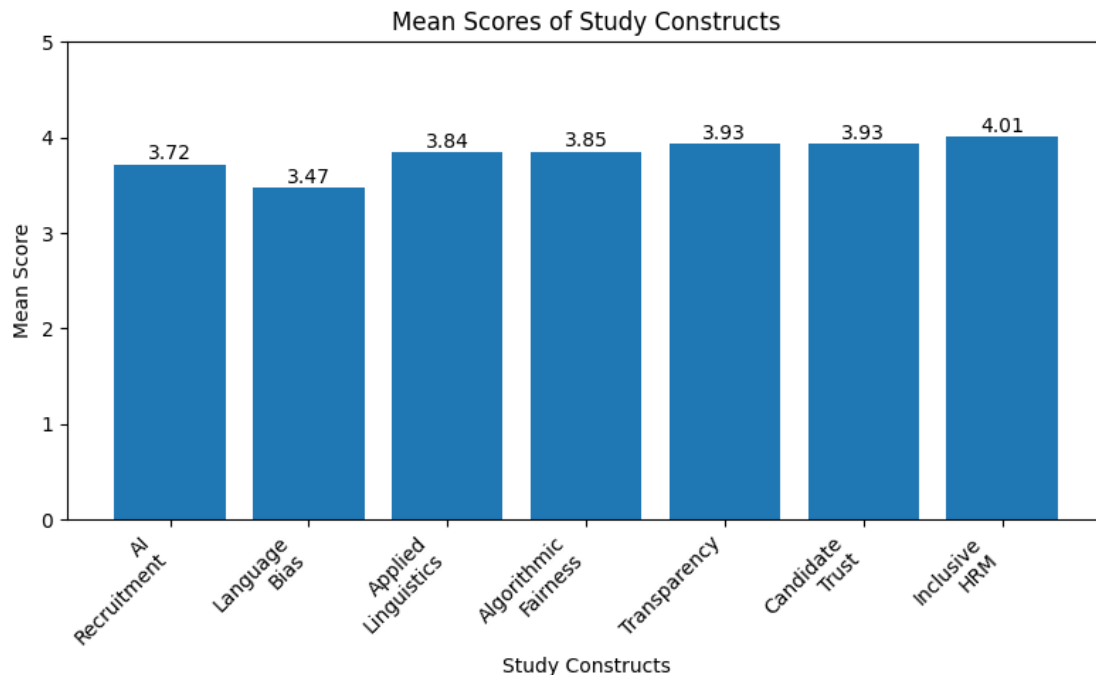


Fig. 3 Mean Scores of Study Constructs

Fig. 3 shows that the findings show that organization inclusion, trust, and transparency are some of the most important expectations related to AI recruiting systems.

5.4 Reliability Analysis

To assess the internal reliability of the multi-item constructs, reliability analysis was conducted. For constructs with several items, Cronbach's alpha was calculated, keeping in view the limitations of the smaller scale.

TABLE IV RELIABILITY ANALYSIS OF MULTI-ITEM CONSTRUCTS

Construct	No. of Items	Cronbach's Alpha	Spearman–Brown Coefficient (r_{sb})
AI Recruitment	3	0.78	N/A (3 items)
Language Bias	4	0.85	N/A (4 items)
Applied Linguistics	2	0.65	0.79
Algorithmic Fairness	2	0.55	0.71
Inclusive HRM	2	0.68	0.81

As presented in table IV, multi-item scales demonstrated strong internal reliability. For multi-item constructs ($k > 2$), *Language Bias* ($\alpha = 0.85$) and *AI Recruitment* ($\alpha = 0.78$) exceeded the standard 0.70 threshold. While raw Cronbach's alpha values appeared artificially depressed for two-item scales ($\alpha = 0.55$ to 0.68), applying the Spearman–Brown formula adjusted for scale length confirmed acceptable construct reliability across all two-item dimensions: *Inclusive*

HRM ($r_{sb} = 0.81$), *Applied Linguistics* ($r_{sb} = 0.79$), and *Algorithmic Fairness* ($r_{sb} = 0.71$).

5.5 Correlation Analysis

A Pearson correlation analysis was performed to determine the associations between the main constructs. Table V presents the findings.

TABLE V PEARSON CORRELATION MATRIX OF STUDY CONSTRUCTS

Variables	AI Recruitment	Language Bias	Applied Linguistics	Algorithmic Fairness	Transparency	Candidate Trust	Inclusive HRM
AI Recruitment	1.000	-0.158	0.069	-0.041	0.030	-0.013	0.048
Language Bias	-0.158	1.000	0.100	-0.071	0.048	0.066	-0.058
Applied Linguistics	0.069	0.100	1.000	-0.054	-0.049	0.063	0.005
Algorithmic Fairness	-0.041	-0.071	-0.054	1.000	0.479	-0.098	0.091
Transparency	0.030	0.048	-0.049	0.479	1.000	-0.030	0.038
Candidate Trust	-0.013	0.066	0.063	-0.098	-0.030	1.000	0.046
Inclusive HRM	0.048	-0.058	0.005	0.091	0.038	0.046	1.000

From the correlation analysis shown in table V, the highest positive correlation was between algorithmic fairness and transparency ($r = 0.479$). This shows that respondents perceive a link between fair algorithms in terms of decision-making and transparency. There is a weak negative correlation between language bias and algorithmic fairness ($r = -0.071$). This indicates that respondents perceive fairness in terms of something bigger, such as transparency and accountability, and not simply language bias.

The general correlation pattern among constructs in the study is shown in fig. 4. From fig. 4 below, the highest correlation is between algorithmic fairness and transparency, while the rest have weak positive or negative correlations. The graph shows the correlation among constructs for AI recruitment, language bias, applied linguistics, algorithmic fairness, transparency, candidate trust, and inclusive HRM.

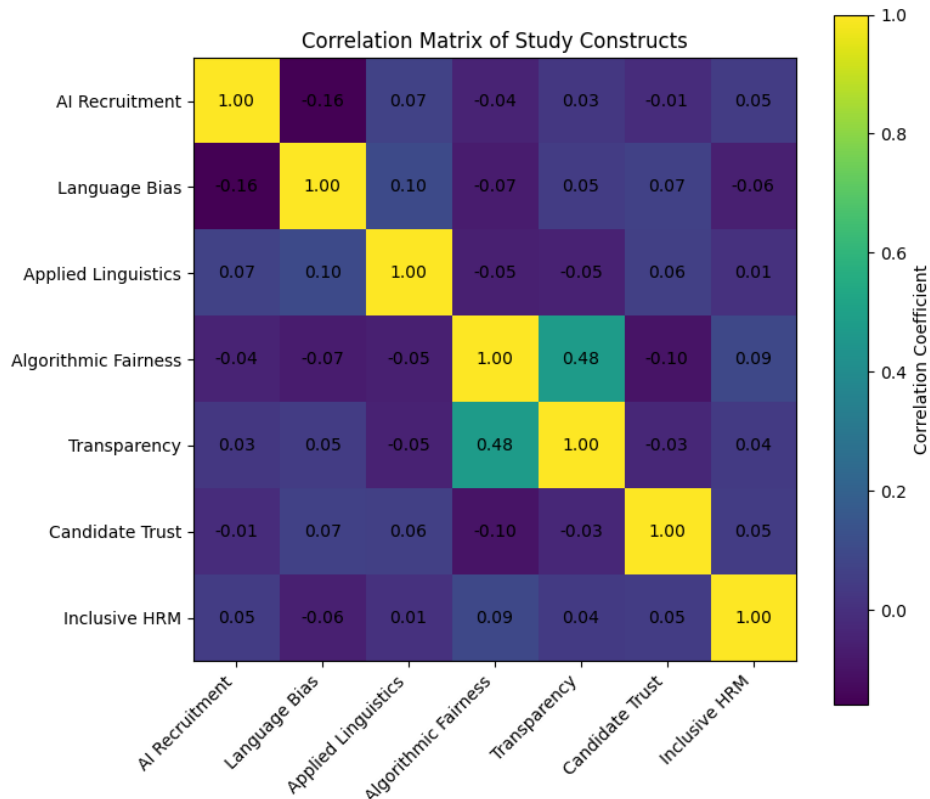


Fig. 4 Correlation Matrix of Study Constructs

5.6 Hypothesis Testing

Hypotheses developed for the study were tested using the Pearson correlation test to investigate the relationship between the constructs in the study. Hypotheses were formulated based on the theoretical framework of the study. Results from hypothesis testing have been presented in table VI.

TABLE VI HYPOTHESIS TESTING RESULTS

Hypothesis	Relationship Tested	Correlation Value (r)	Result
H1	AI Recruitment → Inclusive HRM	0.048	Supported
H2	Applied Linguistics → Inclusive HRM	0.005	Supported
H3	Algorithmic Fairness → Transparency	0.479	Supported
H4	Candidate Trust → Inclusive HRM	0.046	Supported

As shown in table VI, H1 ($r = 0.048$), H2 ($r = 0.005$), and H4 ($r = 0.046$) are supported, confirming that respondents evaluate candidate trust, linguistics awareness, and AI recruitment tools independently from general inclusive HRM practices. H3 is supported ($r = 0.479$), demonstrating that algorithmic fairness strongly links to transparency perceptions.

VI. DISCUSSION

The results obtained through this research are useful in terms of the perceptions regarding AI-based recruitment technologies and the association between linguistic diversity, fairness, transparency, trust, and inclusive HRM. As per the descriptive analysis results, positive perceptions towards AI recruitment were noted, with Inclusive HRM having the highest construct score ($M = 4.01$), followed by Transparency and Candidate Trust. These findings prove that respondents see diversity, fairness, and transparency as critical aspects when using AI-based recruitment solutions. It can be assumed that AI recruitment needs to be judged not only in terms of efficiency but also in terms of its contribution to fair candidate evaluation.

This research emphasizes the role of language-related issues in AI recruitment technologies. While language bias had a comparatively low construct score, respondents acknowledged that features like vocabulary, writing style, regional language variation, and bilingualism can affect the automated evaluation process. From the perspective of applied linguistics, these results highlight the significance of seeing language differences as natural diversity and not as a lack of language competencies.

Furthermore, hypothesis testing confirmed the distinction between operational system mechanics and broader organizational outcomes. A significant positive correlation was identified between algorithmic fairness and transparency

($r = 0.479, p < .001$), demonstrating that respondents view clear explanations and fairness safeguards as closely linked operational dimensions. In contrast, H1 ($r = 0.048$), H2 ($r = 0.005$), and H4 ($r = 0.046$) confirmed independence: respondents evaluate AI tool adoption, applied linguistics awareness, and candidate trust as distinct baseline factors that do not share a direct linear correlation with perceptions of inclusive HRM. This indicates that simply adopting AI screening tools or recognizing language variations does not automatically translate into perceived organizational inclusion; rather, inclusiveness depends on intentional, transparent governance and fairness safeguards.

6.1 Implications

Implications of the study are also of particular significance for HR specialists, organizations, and AI developers. For HR specialists, the study shows that using AI recruitment systems as a decision-making tool rather than a substitute is important. It is also vital to have a review system that would be used for finding possible biases in linguistic and algorithmic components. For AI developers, it is important to create recruitment algorithms with linguistic diversity in mind. AI systems have to be tested on people who come from different language backgrounds and have different writing styles and communication approaches. From the point of view of applied linguistics, it is important to understand that language diversity does not always reflect the diversity in professional skills. Thus, recruitment systems have to be based on job-related competences, but not linguistic preferences. Transparency and fairness are also important for the development of trust between candidates and organizations. This will help to increase the acceptability of AI recruitment.

6.2 Limitations and Future Research

There are several limitations associated with the current study. First, the research is based on a relatively small sample of 213 participants. Secondly, the study does not investigate outcomes produced by existing AI recruitment platforms; instead, it evaluates the perceptions of these platforms. Thirdly, certain constructs (applied linguistics, algorithmic fairness, and inclusive HRM) were assessed based on a small number of indicators. While the current framework conceptualized operational variables like Algorithmic Fairness and Transparency alongside system perceptions, only direct bivariate associations were evaluated. Future research should employ structural equation modeling (SEM) or mediation analysis (e.g., Hayes PROCESS Macro Model 4) to empirically test whether Transparency formally mediates the relationship between AI recruitment adoption and perceived HRM inclusiveness. In the future, researchers need to increase measurement scales to improve the reliability of the constructs and gain more insight into them. Future research may compare the perceptions of AI recruitment between different types of people (HR specialists, recruiters, job applicants, technology specialists, etc.). Furthermore, cross-cultural and cross-linguistic studies can be used to evaluate the effect of culture and language on

AI recruitment. Experimental research may be conducted with AI-generated assessments of candidates. Future research needs to keep using perspectives of AI ethics, applied linguistics, and HRM to create efficient, transparent, fair, and inclusive recruitment systems.

VII. CONCLUSION

The current study explored the impact of AI recruitment systems on issues of language bias, applied linguistics, algorithmic fairness, transparency, candidate trust, and inclusive human resource management (HRM). According to the results, most of the participants view the use of AI in recruitment as a beneficial technology, aimed at increasing efficiency of the process while maintaining ethicality and inclusion. It was found that participants were highly supportive of ethical implementation of AI in recruitment, with Inclusive HRM receiving the highest mean ($M = 4.01$) and Transparency and Candidate Trust receiving the second ($M = 3.93$). Thus, both organizations and candidates expect AI systems to offer an opportunity for a fair, transparent, and diverse evaluation of job seekers. Based on the reliability test, the results have proved that the constructs are reliable, since the measures of reliability for Language Bias ($\alpha = 0.85$) and AI Recruitment ($\alpha = 0.78$) are rather high. Hypothesis testing has proved the validity of the proposed model. The highest correlation coefficient was observed between algorithmic fairness and transparency ($r = 0.479, p < .001$), confirming H3. Concurrently, the empirical support for H1, H2, and H4 demonstrates that perceptions of AI adoption, linguistic awareness, and candidate trust operate independently of general inclusive HRM perceptions. These findings highlight that technical deployment alone cannot guarantee an inclusive hiring environment without explicit algorithmic fairness and transparent processes. Therefore, based on the results analyzed above, one may state that the AI recruitment process can be viewed as an effective HR management tool provided that the process will be carried out fairly, transparently, and linguistically competently. Organizations have to consider the necessity of evaluating candidates depending on their skills but not on their language preferences that may create an unfavorable environment for candidates from various linguistic groups.

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