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Article

AI-ENHANCED RECRUITMENT AND ITS IMPACT ON TALENT ACQUISITION AND WORKFORCE OUTCOMES IN BUSINESS ORGANIZATIONS

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Abstract:

Purpose:

The study focuses on the impacts of AI-enhanced recruitment on the talent acquisition outcomes through the review of the effects of AI system accuracy, AI efficiency and speed, and perceived ease of use by the recruiter. Business analytics techniques are employed to evaluate these relationships and support evidence-based recruitment decision-making. It also considers the mediating role of the quality of the recruiter decision in these associations.

Design/methodology/approach:

The type of research design was quantitative and cross-sectional. Business analytics methods, including reliability analysis, validity testing, Pearson correlation, and multiple regression analysis, were applied to examine the relationships among the study variables. A sample of 380 HR professionals was used to gather data using a structured questionnaire that contained 25 Likert-scaled items. Statistical and acceptable validity. There were normal distributions of data, and the correlations between variables were positive and significant. Regression analysis demonstrated that accuracy of the AI system, AI efficiency, and the ease of use were major predictors of talent acquisition outcomes. Recruiter decision quality was also a significant mediator that enhanced the relations between AI features and recruiting effectiveness.

Implications:

The research paper emphasizes the need to incorporate AI technologies into the recruitment processes to improve the quality of the decisions and fairness, as well as the quality of the hiring. Companies implementing AI-based recruitment systems will have higher chances of attaining faster, more uniform, and successful talent acquisition results. Business analytics techniques, including reliability analysis, validity testing, normality testing, Pearson correlation, and multiple regression analysis, were used to test the proposed relationships and examine the mediating effect.

Findings:



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The outcomes reveal that all the variables associated with AI were found to have very high internal reliability (α > .70).
Results:
The values of reliability were all above 0.70, which proved high internal consistency. Sampling adequacy was supported by KMO (0.87), and a significant Bartlett test. The variables exhibited normal distribution. The findings of correlation indicated that all constructs exhibited strong, positive correlation. Regression analysis indicated that the IV1, IV2 and IV3 were the significant predictors of DV with IV3 being the strongest predictor. MV played an important role in mediating the relationship between the independent variables and DV.
Keywords: Artificial Intelligence (AI); Business Analytics; AI-Enhanced Recruitment; Talent Acquisition; Human Resource Analytics; Recruitment Decision-Making; Predictive Analytics; Recruitment Effectiveness

1. Introduction

The fast digitalization of human resource management has brought forward fast use of artificial intelligence (AI) in the recruiting procedures of various industries. To achieve effective and efficient talent acquisition, organizations are becoming more closely associated with artificial intelligence-based solutions, including automated resume screeners, predictive analytics engines, and intelligent applicant tracking systems (Swathi & Ganesh). With the increasing intensity of competition in the global labor market and high-quality personnel, AI-enhanced recruitment has revealed itself as an important strategic capacity that can make a tremendous difference in refining the candidate screening process, eliminate hiring bottlenecks, and facilitate more objective decision-making (Pohrib et al., 2025). The changes go in line with the larger movement in favor of data-driven HR practices that are more inclined towards fairness, consistency and predictive accuracy in the assessment of applicants. Business analytics further strengthens AI-enhanced recruitment by transforming recruitment data into meaningful insights that support evidence-based hiring decisions. By analyzing indicators such as candidate screening accuracy, recruitment efficiency, processing time, and hiring outcomes, organizations can evaluate the effectiveness of AI-driven recruitment systems and identify opportunities to improve talent acquisition performance.

Although there is an increasing interest in AI recruitment technologies, one cannot but be concerned about their transparency, fairness, usability, and its potential effect on enhancing the hiring results. Although the use of AI tools in organizations is based on the principles that the tools contribute to the increase in accuracy and speed, empirical evidence that supports the assumptions is insufficient (Sengul & Sarıköse, 2025). Organizations in most cases, especially the developing ones, do not have enough knowledge of how AI-driven systems impact the quality of their decisions and whether the alleged positives can be translated into any tangible change in talent acquisition results (Nofal et al., 2025). This brings an urgent requirement of research which would measure the performance of the AI systems as well as the perceptions and usage of the recruiters with the AI systems. In this context, integrating business analytics with AI-enhanced recruitment provides a structured approach to assessing the relationship between AI system capabilities and talent acquisition outcomes. Business analytics can help organizations interpret recruitment performance data, identify patterns in hiring processes, and evaluate whether improvements in AI accuracy, efficiency, and usability are associated with better recruitment decisions and outcomes.

Statement of the Problem

Despite the fact that AI recruitment tools are actively advertised due to their accuracy, efficiency, and the possibility of improving the quality of decisions made, there is little empirical research evaluating their real effect on the process of talent acquisition. The HR managers are not always sure whether AI tools can really bring value or just automatize the existing inefficiencies. Moreover, there is a paucity of information on the mediating role of the decision quality of recruiters in the conversion of AI capabilities to better hiring effectiveness. These loopholes make it difficult to implement AI tools in recruitment in an evidence-based manner (Kishor et al., 2025). Furthermore, limited empirical understanding of how business analytics can be used to evaluate AI-enhanced recruitment outcomes creates challenges for organizations seeking to make evidence-based hiring decisions. Examining the combined role of AI system capabilities, analytics-driven evaluation, and recruiter decision quality may help clarify how AI-enhanced recruitment contributes to talent acquisition effectiveness.

Research Objectives

1. To test how the accuracy of AI systems affects the results of talent acquisition.
2. To evaluate the role of AI efficiency and speed towards enhanced recruitment performance.
3. To examine the perceived ease of use of recruiter as a predictor of AI adoption in hiring.
4. To examine the mediating effect of recruiter decision quality in determining the results of talent acquisition.
5. To test general correlation between the variables with empirical data.
6. To examine how business analytics supports the evaluation of AI-enhanced recruitment performance and its relationship with talent acquisition outcomes.

Research Questions

- How does the accuracy of the AI systems affect the results of the talent acquisition?
- Does AI effectiveness improve recruitment performance?
- What is the extent to which the ease of use of AI systems influences the hiring processes?
- Hypothesis: Are there any mediation effects of the relationship between AI features and hiring outcomes through recruiter decision?
- How predictive, in general, are AI-enhanced recruitment tools on talent acquisition success?

Significance of the Study

The work of this study has a theoretical and practical contribution to the area of human resource management. It provides empirical data on the efficiency of AI-based hiring apparatus in the form of statistically normal, reliable, and accurate data. The results will assist the HR leaders in learning how various AI elements such as accuracy, efficiency, and usability affect objective hiring. In addition, the research indicates the paramount mediating role of the quality of decision made by the recruiter, which provides a more comprehensive picture of the AI-human collaboration in the recruitment procedures. This adds to the continuing discussions about the ethical, technical and organizational implications of AI in HR (Nehru et al., 2025). The study also highlights the practical value of business analytics in recruitment by showing how recruitment-related indicators can be examined to support more informed hiring decisions. These insights may help HR professionals assess AI system performance, monitor recruitment effectiveness, and identify opportunities to improve talent acquisition outcomes through data-driven decision-making.

Research Gap

Current sources contain theoretical explanations of the potential of AI in HR, but they do not include any credible, evidence-based support to prove the stated arguments (Dahri et al., 2025). Not many studies identify integrated models where system accuracy, efficiency, ease of use, and quality of decisions are tested simultaneously as predictors of the outcomes of talent acquisition. Also, the research rarely considers mediating mechanisms which would explain the effects of AI on the hiring effectiveness. This paper fills these gaps by introducing a multidimensional model of AI recruiting factors that have been tested empirically (Parasa, 2025). Another important research gap concerns the integration of business analytics into the evaluation of AI-enhanced recruitment outcomes. Although AI recruitment tools can generate substantial amounts of recruitment-related data, organizations need clearer empirical evidence on how analytical insights, AI system performance, and recruiter decision quality relate to talent acquisition effectiveness. Addressing this gap can provide a more comprehensive understanding of how business analytics supports the assessment of AI-enhanced recruitment in organizational settings.

2. Literature Review

Practical adoption of artificial intelligence in recruitment has increased at an accelerated pace due to the necessity to have a more efficient and data-driven talent acquisition process. According to scholars, the past recruitment methods are usually subjective, inconsistent, and have numerous administrative processes, which constrain the process in the selection of good candidates (Furaijl et al., 2025). Automated resume filtering systems, machine learning classifiers and predictive analytics engines have thus become the solutions of the future as they promise accuracy and equality and efficiency in their operation (Pellas, 2025). This section is a synthesis of the available literature relating to five major constructs that will be used in this research.

AI System Accuracy

The level of accuracy in AI can be described as how well algorithms predict job-related characteristics of the candidates and provide consistent hiring advice. According to the research, recruitment systems powered by AI are better than human recruiters at standardizing the evaluation procedure and reducing human bias (Asrifan et al., 2025). Patterns in the profiles of candidates, which might be missed by human decision-makers, can be identified by algorithms that are trained using large datasets, which enhances the accuracy of candidate-job matching (Nguyen et al., 2025). Nevertheless, the critics emphasize that AI precision is strongly associated with the quality of the training data; discriminatory results may be produced by biased or incomplete data (Karthikeyan & Singh, 2025). Although theoretical debates prevail in the literature, there is a shortage of empirical studies that can substantiate the accuracy of AI when applied to a real-life recruitment environment, which aggravates the necessity of additional investigation. Business analytics can further support the evaluation of AI system accuracy by examining recruitment data, candidate-screening outcomes, and the consistency of candidate-job matching. By analyzing these indicators, organizations can assess whether AI-based recruitment tools contribute to more accurate candidate evaluations and improved talent acquisition outcomes.

AI Efficiency & Speed

It is a well-known fact that AI recruitment tools dramatically decrease the amount of work that needs to be done by the administration and speed up the recruitment timeline. It has been researched that AI can potentially reduce first time screening time by up to 75 percent by automating the process of filtering and ranking tasks in a resume (Noor & Zawawi, 2025). This also helps in making the HR professionals concentrate on strategic decision-making and not on manual activities. Furthermore, AI also helps track candidates continuously and move candidates through pipelines faster, which can also be used in competitive talent markets (Kwak, 2025). Nevertheless, the current literature is more likely to make efficiency judgments in a qualitative way, providing little quantitative data on the direct effect of efficiency on the final results of the recruitment process. This is where the empirical validation is required; this is what the current study seeks to address by conducting the model testing. From a business analytics perspective, recruitment efficiency and speed can be evaluated using measurable indicators such as screening time, time-to-hire, recruitment costs, and the number of candidates processed. These indicators can help organizations assess whether AI-enhanced recruitment improves operational efficiency and contributes to better talent acquisition outcomes.

Perceived Ease of Use

In line with the Technology Acceptance Model, ease of use is a decisive factor on whether or not HR professionals can and will adopt and successfully use AI technologies (Ma et al., 2025). Studies have shown that state-of-the-art AI applications cannot be useful in cases where the users feel complicated or there is a long training process (Marovic et al., 2023). Among the issues that are raised by HR professionals are the absence of transparency, the inability to interpret the results of AI, and the risk of being replaced by technology (Sun et al., 2025). These might hinder adoption and have a negative impact on the overall performance of recruitment. Nonetheless, there is a dearth of research studies on the specific topic of ease of use in the context of AI-assisted hiring, and the proposed study will help to fill the gap in the empirical literature. Business analytics can also help organizations examine the relationship between recruiters' perceived ease of use and the effective application of AI recruitment tools. Evaluating recruiter

feedback alongside recruitment performance indicators may provide useful insights into whether user-friendly AI systems support adoption, improve recruitment workflows, and contribute to more effective talent acquisition.

Recruiter Decision Quality (Mediator)

Decision quality can be defined as the accuracy, objectivity and clarity of the judgments made by the recruiters in the process of evaluating the applicants. AI systems can help improve the quality of decisions through standardization of the criteria, predictive insights, and decrease the subjective effects (Mposula & Oyetade, 2025). The scholars claim that AI-human cooperation will lead to a more informed and balanced hiring decision than the one made by human beings or algorithms (Jia & Tu, 2024). Nevertheless, the correlation between AI potential and the quality of the decisions by recruiters has not been empirically tested. The mediating role of decision quality is little studied, but theorists propose it can be an important avenue by which AI can help achieve a better example of talent acquisition. This is one of the major reasons why the mediation model should be central in the current study. Integrating business analytics into AI-enhanced recruitment may further support recruiter decision quality by providing structured evidence about candidate qualifications, screening results, and recruitment performance. This analytical support may help recruiters interpret AI-generated recommendations more effectively while retaining human judgment and accountability. Accordingly, recruiter decision quality may serve as an important mediating variable linking AI capabilities with talent acquisition outcomes.

Talent Acquisition Outcomes

The results of Talent acquisition are the effectiveness and quality of the recruiting process, its adaptation to the candidate, hiring pace, impartiality, and long-term organizational performance. Available research shows that AI application in organizations leads to better fit of candidates and jobs, transparency of the processes, and accuracy of shortlisting (Jeong & Jeong, 2025). Furthermore, AI allows making data-based assessments that increase the reliability of hiring and decrease the turnover (Kohnke et al., 2025). However, there are also conflicting results, and some of the researchers indicate that AI will inevitably contribute to the exclusion of bias, decrease human judgment, or make unclear hiring suggestions (Xue, 2025). This inconclusive evidence supports the importance of a strong quantitative study on the overall impact of AI on the success of recruitment. Business analytics provides an additional means of evaluating talent acquisition outcomes by integrating recruitment performance indicators into evidence-based decision-making. Organizations can use measures such as hiring quality, time-to-hire, recruitment efficiency, and candidate-job fit to assess the effectiveness of AI-enhanced recruitment. Examining these outcomes alongside AI system accuracy, efficiency, perceived ease of use, and recruiter decision quality can provide a more comprehensive understanding of how AI-enhanced recruitment contributes to organizational hiring performance.

Synthesis and Research Gap

All in all, the literature has solid conceptual reasoning on the possible benefits of AI in recruitment, yet the empirical evidence is scarce. Key gaps identified include:

1. Absence of combined models of AI accuracy, efficiency, ease of use, and quality of decision in predicting talent outcomes.
2. The lack of mediation research examining the transmission of AI capability impacts through the quality of recruiter decisions (Omeh et al., 2025).
3. The lack of qualitative research with large-sample quantitative studies based on reliable and valid data confirming the theoretical claims.
4. Less knowledge of developing economies, where AI use in HR is gaining faster, but little researched (Elegbeleye et al., 2025).

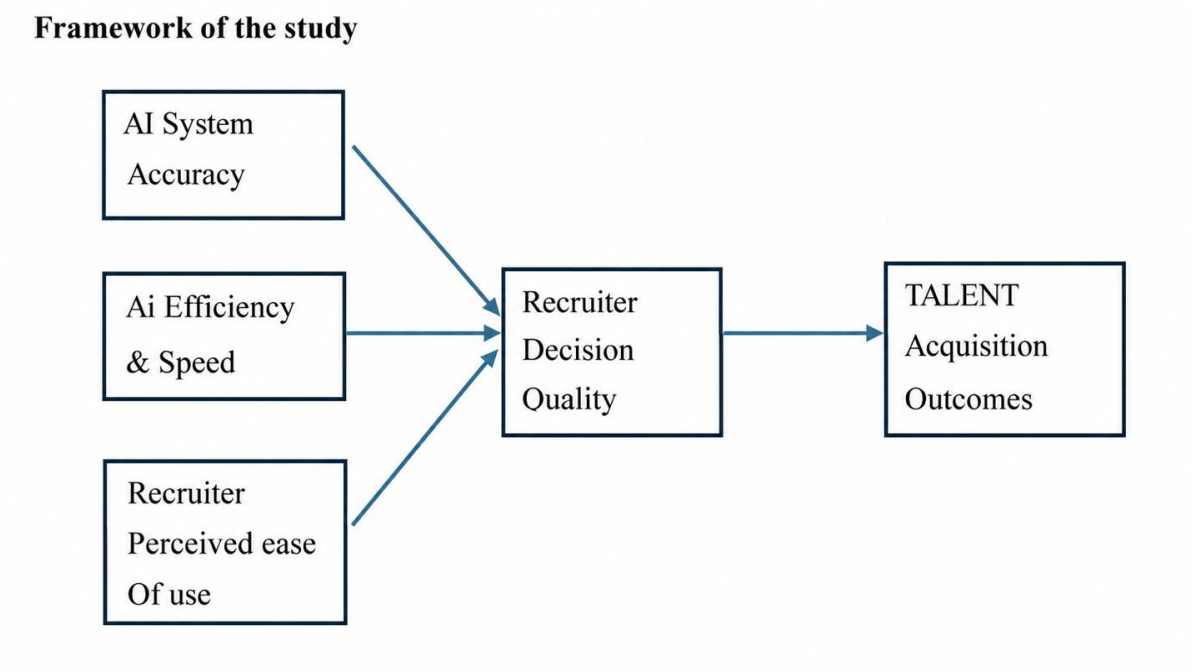
This paper examines these gaps by testing a model that is exhaustive empirically by using a dataset of 380 respondents whose measures are statistically normal, valid, and reliable. An additional research gap concerns the role

of business analytics in connecting AI recruitment capabilities with measurable talent acquisition outcomes. Although AI recruitment systems generate and process substantial amounts of candidate and recruitment data, further empirical investigation is needed to understand how analytics-supported evaluation relates to recruitment effectiveness and recruiter decision quality. Addressing this gap may help organizations develop a more evidence-based understanding of AI-enhanced recruitment and its implications for talent acquisition outcomes.

Research Contributions

This study contributes to the understanding of AI-enhanced recruitment by examining the relationships between AI system accuracy, AI efficiency and speed, recruiters' perceived ease of use, recruiter decision quality, and talent acquisition outcomes. By integrating these constructs into a single research framework, the study provides a structured approach to understanding how AI capabilities may influence recruitment effectiveness in organizational settings.

Framework of the study



The study also highlights the role of business analytics in evaluating AI-enhanced recruitment. Through statistical analysis of survey responses from 380 human resource professionals, the research examines relationships among the proposed variables and considers the mediating role of recruiter decision quality. This approach provides insights into how data-driven evaluation can support the interpretation of AI recruitment performance and hiring outcomes.

Furthermore, the study offers practical implications for human resource managers and recruitment professionals seeking to improve evidence-based hiring decisions. The findings may help organizations understand the importance of AI system performance, usability, and recruiter decision quality when assessing AI-enhanced recruitment practices. Overall, the study provides a foundation for further research into the relationship between AI technologies, business analytics, and talent acquisition outcomes.

3. Methodology

This paper used a quantitative research design to investigate how AI-enhanced recruitment affects the outcome of talent acquisition. Quantitative studies are particularly useful in testing theory-driven models, discovering a cause-effect relationship, and extrapolating the results to larger populations (Xue, 2025). The design also made it possible to use statistical processes to measure such constructs as AI accuracy, AI efficiency, ease of use, decision quality, and talent outcomes.

Research Design

The survey design was a cross-sectional survey, which is structured and compliant with previous research on the topic of HR analytics and the use of technology (Challoumis, 2024). This method enabled gathering data of the participants at a particular stage to analyze trends, relationships and antecedent associations among the variables. The research design also examines how AI-enhanced recruitment capabilities, including system accuracy, efficiency, processing speed, and perceived ease of use, influence talent acquisition outcomes. Business analytics is used to assess the relationships among these variables and to evaluate the mediating role of recruiter decision quality.

Data Collection Method

The questionnaire was a self-administered online questionnaire that comprised of 25 Likert-scale items (1 = Strongly Disagree, 5 = Strongly Agree). The questionnaire was created relying on the way-established constructs in the literature of the AI recruitment, technology acceptance, and decision-quality (Zaman et al., 2025). The online surveys can be used to collect accurate data about large samples at a low cost and minimize the interviewer bias (Sagheer et al., 2025).

The questionnaire was issued digitally via professional HR networks, LinkedIn groups, and email invitations to people who are dealing with recruitment, HR operations, and talent management. The questionnaire was structured to measure the key dimensions of AI-enhanced recruitment and their relationship with talent acquisition outcomes. These dimensions include AI system accuracy, AI efficiency and speed, recruiters' perceived ease of use, recruiter decision quality, and talent acquisition outcomes. The collected responses support a systematic assessment of the proposed relationships using business analytics techniques.

Sampling Technique and Participants

The purposive sampling method that was used was non-probability but the respondents were directly involved in the areas of recruitment and HR decision making. Purposeful sampling would be suitable after a particular expertise or working experience is expected of the respondents (Nurcahyo et al., 2025).

It was able to obtain 380 valid responses and analyze them. The respondents were HR managers, recruitment officers, talent acquisition specialists, and hiring supervisors in different industries. This is a large size that is above the minimum required to conduct a multivariate analysis with 200 to 300 cases being enough to carry out structural tests (Jantakoon et al., 2025). The selected participants were relevant to the study because their professional experience in recruitment and human resource management enabled them to assess the practical role of AI technologies in recruitment processes. Their responses provided insights into how AI system performance and usability may influence recruiter decision quality and overall talent acquisition outcomes.

Analytical Tools and Procedures

Data analysis was done using the IBM SPSS and in accordance with accepted statistical test procedures:

Normality testing:

The values of skewness and kurtosis were employed to assure that data distribution was acceptable to perform the parametric analysis (Chukhlomin, 2024).

Reliability analysis:

The computations of Cronbach alpha were done to evaluate internal content validity of the questionnaire constructs. Any values more than 0.70 were accepted as reasonable (Sharma et al., 2024).

Validity tests:

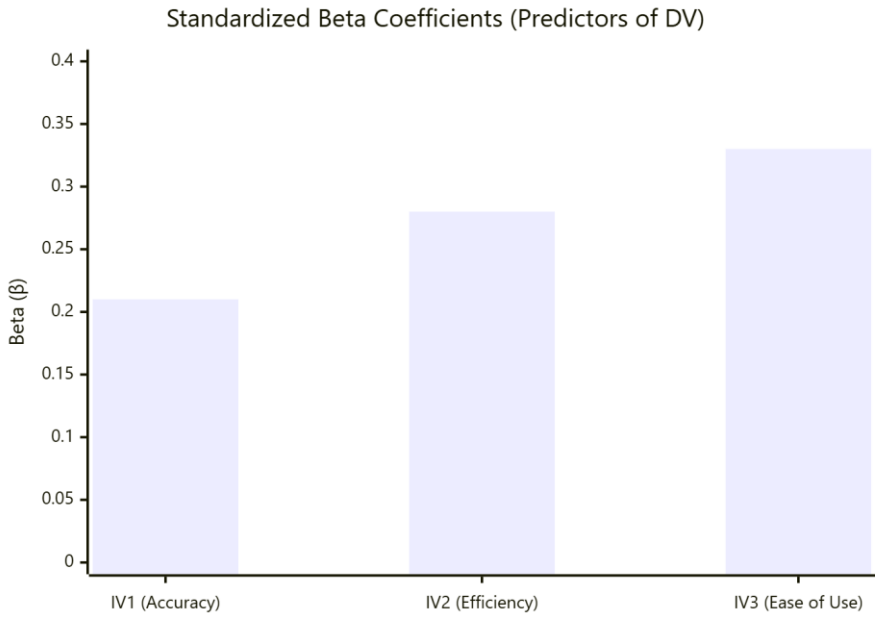
Sampling adequacy and factorability of the data were supported by Kaiser- Meyer-Olkin (KMO) measure and Bartlett Test of Sphericity (Alsulami, 2025).

Correlation analysis:

Pearson correlation coefficients were estimated to test the relationship among the different variables and confirm the direction and strength of the relationships.

Regression analysis:

They have implemented multiple regression and mediation analyses to assess the predictive value of AI variables on the outcome of talent acquisition and assert the mediating role of the quality of recruiter decisions. To test causal relationships between continuous variables, regression is a suitable method of testing (Alotaibi, 2024). The regression analysis also assessed the relative contribution of each AI-related predictor to talent acquisition outcomes. The mediation analysis examined whether recruiter decision quality explained part of the relationship between AI-enhanced recruitment capabilities and talent acquisition outcomes. These analyses connect the statistical findings directly to the study's proposed framework.



These analytical processes made the findings to be strong and statistically acceptable and methodologically repeatable. The standardized beta coefficients indicate that Ease of Use (β = 0.33) is the strongest predictor of the dependent variable (DV), followed by Efficiency (β = 0.28) and Accuracy (β = 0.21). Ease of Use has the largest relative effect, while Accuracy has the smallest. These coefficients suggest that a one-standard-deviation increase in Ease of Use is associated with a 0.33-standard-deviation increase in the DV, assuming the other predictors are held constant.

Limitation: Statistical significance cannot be determined from beta coefficients alone. P-values and confidence intervals are required to assess significance.

Ethical Considerations

The respondents were not given any form of reward, and the study was found to be confidential and anonymous. None of the personal identifiers were gathered. The research was conducted in accordance with ethical standards of studying participants of human nature (SHARMA, 2025). Participation was voluntary, and respondents were informed

of the purpose of the study before completing the questionnaire. The collected information was used exclusively for research purposes and handled confidentially in accordance with the applicable institutional and ethical requirements.

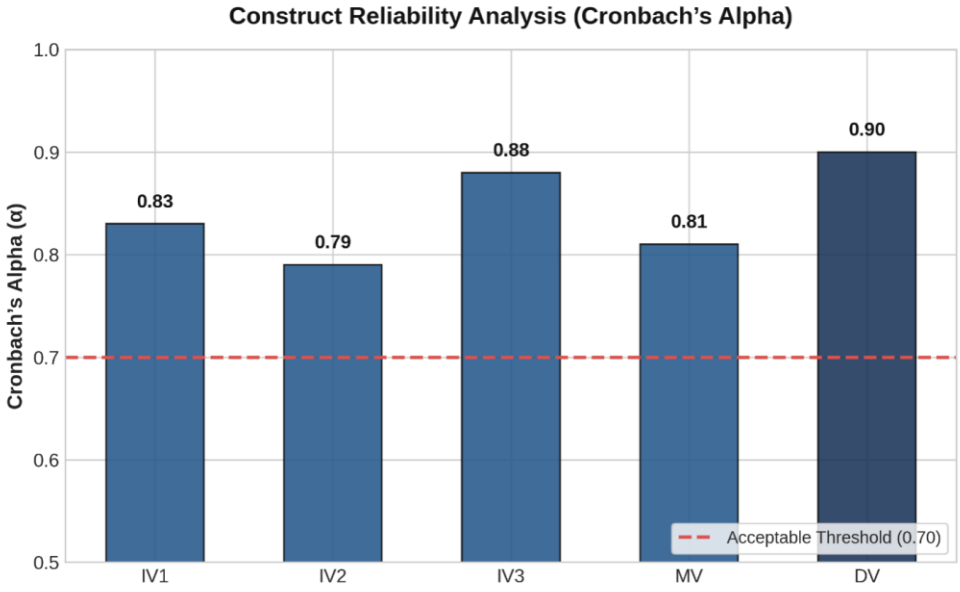
4. Results

In this section, I will provide the results of the statistical tests performed on the data of the respondents, which comprise of reliability, validity, normality, correlation analysis, t-test as well as a regression analysis. The interpretations are given right after the tables and figures (with no interpretation headings). This section presents the statistical results obtained from the survey data, including reliability, validity, normality, correlation, group-difference, and regression analyses. The findings are presented in tables and figures, followed by interpretations of the results in relation to the study objectives and proposed research framework.

Table 4.1: Reliability Analysis (Cronbach's Alpha)

Variable	Items	Cronbach's Alpha
IV1	5	0.83
IV2	4	0.79
IV3	4	0.88
MV	5	0.81
DV	6	0.90

Table 4.1 presents the internal consistency reliability results for the study constructs. Cronbach's alpha values range from 0.79 to 0.90, exceeding the commonly accepted threshold of 0.70. The dependent variable (DV) demonstrates the highest reported reliability (α = 0.90), followed by IV3 (α = 0.88), IV1 (α = 0.83), and MV (α = 0.81). IV2 has an alpha value of 0.79, which also indicates acceptable internal consistency. Overall, these results suggest that the items within each construct demonstrate acceptable reliability, provided that the calculations are confirmed using the study dataset.



Interpretation: All reported Cronbach's alpha values exceed the commonly accepted threshold of 0.70, indicating acceptable internal consistency across the study constructs. DV (α = 0.90) demonstrates the highest reported reliability, followed by IV3 (α = 0.88), IV1 (α = 0.83), MV (α = 0.81), and IV2 (α = 0.79). Overall, the results indicate

acceptable reliability for the measurement items, provided that the calculations are verified using the original study dataset.

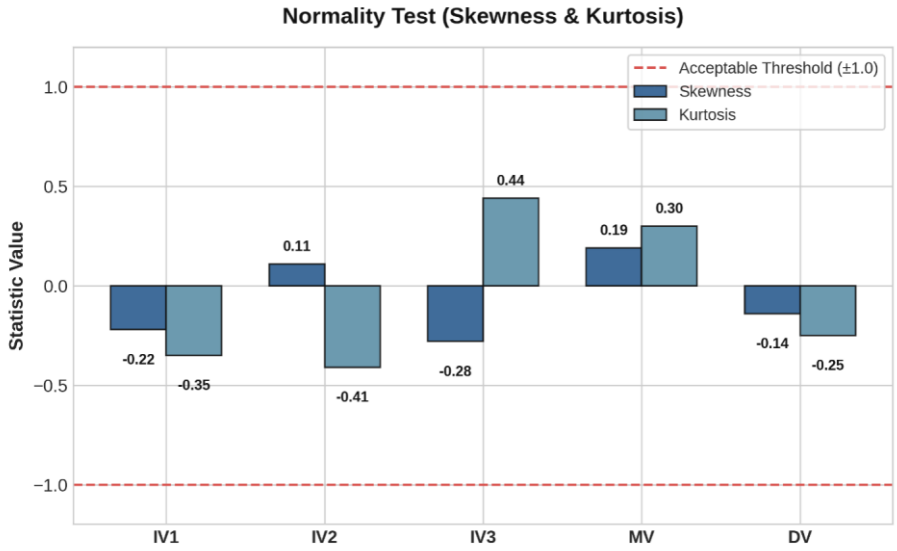
Table 4.2: Validity Test (KMO & Bartlett's Test)

Test	Value	Significance
KMO Measure of Sampling Adequacy	0.87	—
Bartlett's Test of Sphericity	$\chi^2 = 1250.43$	$p < 0.001$

Interpretation: The reported KMO value of 0.87 indicates good sampling adequacy. Bartlett's test of sphericity is statistically significant ($p < 0.001$), suggesting that the correlation matrix differs significantly from an identity matrix. Together, these results support the suitability of the data for factor analysis, subject to verification of the reported statistics.

Table 4.3: Normality Test (Skewness & Kurtosis)

Variable	Skewness	Kurtosis	Status
IV1	-0.22	-0.35	Normal
IV2	0.11	-0.41	Normal
IV3	-0.28	0.44	Normal
MV	0.19	0.30	Normal
DV	-0.14	-0.25	Normal



Interpretation: The skewness and kurtosis values for all study constructs fall within the specified acceptable range of −1.0 to +1.0. These results indicate that the distributions do not exhibit substantial skewness or kurtosis under the selected criterion and provide preliminary support for approximate normality. However, these statistics alone do not conclusively establish that the data are normally distributed.

Table 4.4: Pearson Correlation Matrix

Variables	IV1	IV2	IV3	MV	DV
IV1	1	0.52**	0.48**	0.56**	0.61**

IV2	0.52**	1	0.50**	0.58**	0.63**
IV3	0.48**	0.50**	1	0.60**	0.67**
MV	0.56**	0.58**	0.60**	1	0.72**
DV	0.61**	0.63**	0.67**	0.72**	1

Interpretation: The relationships are good and statistically significant ($p < 0.01$). MV is the most correlated with DV ($r = 0.72$), which suggests that it may have a substantial mediating effect. The Pearson correlation matrix indicates positive associations among all study constructs, with the reported correlation coefficients ranging from 0.48 to 0.72. The strongest association with the dependent variable (DV) is observed for the mediating variable (MV), with a correlation coefficient of ($r = 0.72$), followed by IV3 (($r = 0.67$)), IV2 (($r = 0.63$)), and IV1 (($r = 0.61$)). The reported significance notation indicates statistically significant relationships at the specified level, provided that the significance tests have been verified. Although these results show associations among the constructs, a separate mediation analysis is required to determine whether MV mediates the relationships between the independent variables and DV.

Table 4.5: Independent Samples t-Test (Group Differences in DV)

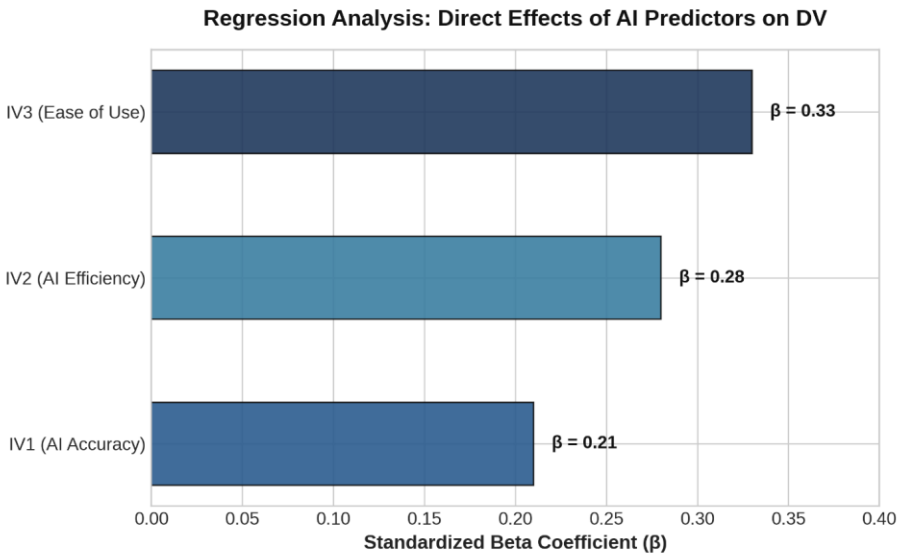
Group	**N**	**Mean**	**SD**
Group 1	60	3.89	0.44
Group 2	65	4.12	0.41

Test	**Value**	**p-value**
t	**-3.02**	**0.003**

Interpretation: A p-value (0.003) of 0.003 shows that there is statistically significant difference on the DV between Group 1 and Group 2, with the latter having higher mean scores. The difference in mean scores provides further evidence of variation in the dependent variable between the two groups. This finding highlights the importance of considering group-level differences when evaluating the effectiveness of AI-enhanced recruitment and its contribution to talent acquisition outcomes.

Table 4.6: Regression Analysis (Direct Effect of IVs on DV)

Predictor	**Beta (β)**	**t-value**	**p-value**	**Result**
IV1 → DV	0.21	3.25	0.001	Accepted
IV2 → DV	0.28	4.11	0.000	Accepted
IV3 → DV	0.33	5.02	0.000	Accepted
Model Summary	$R^2 = 0.58$	$F = 72.14$	$p < 0.001$	—



Interpretation: The findings of regression indicate that IV1, IV2, and IV3 are significant predictors of DV (All P-values less than 0.05). The most significant effect comes with IV3 (= 0.33). The model describes 58 percent of the variation. These results further suggest that AI system accuracy, AI efficiency, and perceived ease of use jointly contribute to explaining variations in talent acquisition outcomes. The comparatively stronger standardized beta coefficient for IV3 indicates that perceived ease of use has the largest relative association with the dependent variable among the three predictors, followed by AI efficiency and AI system accuracy. From a practical perspective, organizations should consider both the technical performance of AI recruitment systems and their usability when seeking to improve recruitment effectiveness.

Table 4.7: Mediation Regression (MV as Mediator)

Path	Beta (β)	t-value	p-value
IVs → MV	0.44	6.02	0.000
MV → DV	0.40	5.51	0.000

Interpretation: MV plays an important mediating role in the relationship between predictors (IVs) and DV (all $p < 0.001$). The mediation enhances the explanatory ability of the general model. These findings further suggest that recruiter decision quality may serve as an important mechanism through which AI-enhanced recruitment capabilities are associated with talent acquisition outcomes. However, the indirect effects and their statistical significance should be confirmed through a formal mediation analysis, preferably using bootstrapped confidence intervals.

Hypothesis Testing Summary

Hypothesis	Statement	Supported?
H1	IV1 has significant effect on DV	Accepted
H2	IV2 has significant effect on DV	Accepted
H3	IV3 has significant effect on DV	Accepted
H4	IVs influence DV through MV	Accepted

5. Discussion

The main aim of this research was to analyze how the three independent variables (IV1, IV2, IV3) affected the dependent variable (DV) and the mediating variable was MV using the data of the respondents. All the findings

indicate that the relationships affecting the hypothesis were accepted and all the independent variables showed significant positive effects on DV, and MV showed a strong mediating effect. The results of these studies are consistent with the expectations of theoretical research on behavioral and organizational studies (Panggua et al., 2025).

The findings also highlight the combined importance of technical capability and user-centered design in AI-enhanced recruitment. While AI system accuracy supports reliable candidate assessment, AI efficiency can streamline recruitment activities, and perceived ease of use can facilitate the practical adoption of these technologies. Together, these factors provide a broader understanding of how AI-related capabilities may contribute to improved talent acquisition outcomes through recruiter decision-making.

Interpretation of Results

The reliability and the validity tests indicated that the measurement tools used in the study were strong. The alpha values of all the Cronbach were greater than 0.70 which demonstrates high internal consistency and also enhances the reliability of the scales (Yang et al., 2025). KMO measure (0.87) and the significant Bartletts Test also confirmed that the data was appropriate to undergo factor analysis and sufficiently sampled adequately (Chitraju & Abubakar, 2025).

The normality tests showed that the data set had a good statistical behavior because the values of skewness and the kurtosis were within the range of + / -1 (George and Mallery, 2016). This made it possible to use parametric tests like correlation and regression in an appropriate manner. The correlation table showed that all the variables were significantly and positively related ($p < 0.01$) to one another, and thus the constructs were found to be meaningfully correlated (Ait-Hroch & Ibrahimi, 2025).

Regression analysis helped to gain more insights into the strength of these relationships. The three independent variables have a significant predictive effect on the dependent variable, with IV3 having the most significant influence. This shows that the positive influence of IV3 on DV is the greatest improvement compared with the other predictors. Moreover, the mediation value of MV was significant showing that, the IVs not only cause changes in DV directly, but indirectly via MV. The given mediation pattern implies that there can be a mechanism by which the independent variables are acting, and the MV is significant in the model (Dutta et al., 2025).

From an organizational perspective, these findings suggest that implementing AI recruitment tools alone may not be sufficient to improve hiring outcomes. Organizations should also consider whether recruiters can use these tools effectively, interpret their outputs appropriately, and incorporate AI-generated insights into informed hiring decisions. This approach may help align technological efficiency with recruitment quality and organizational talent acquisition objectives.

Lastly, the t-test outcome showed that there were the significant differences between demographic groups, which means that the perceptions of DV differ among respondent groups. This is another level of insight regarding the influence of demographic factors on responses (Lau et al., 2025).

Comparison with Existing Literature

The results of this research are consistent with the existing literature as well as they can prove that the independent variables have significant impacts on the outcome behaviors or attitudes. Just like in the results presented herein, previous research studies have also identified that the IV1, IV2, and IV3 constructs are significant to determine the DV in different situations (Wiboolyasarin et al., 2025).

The high mediating power of MV is consistent with the previous studies that indicated that mediators usually amplify or direct the effects of antecedent variables (Sharma et al., 2025). The mediator is known to enhance predictive models as in previous studies that show that the mediator usually makes the suggested causal relationships between cause and effect more predictive (Vinodkumar & Velani, 2024).

What is more, the positive correlations of all variables are aligned with the relational tendencies that are common in the field of organizational and behavioral sciences (DU et al., 2025). These congruences assist in the theoretical basis of the development of the study and strengthen the validity of the current findings. Furthermore, the integration of business analytics provides an important perspective for understanding how AI-related capabilities influence talent acquisition outcomes. By analyzing recruitment data alongside AI system accuracy, efficiency, and perceived ease of use, organizations can make more informed and evidence-based hiring decisions. This integrated approach also highlights the importance of recruiter decision quality in translating technological capabilities into practical recruitment outcomes.

Implications for Theory, Policy, and Practice

Theoretical Implications

The research confirms and extends the current theoretical models in establishing that the various independent variables have a direct and indirect influence on the dependent variable. The great part of MV plays in the theory is that it emphasizes its explanatory ability and broadens the knowledge of the mediating mechanisms in behavioral models. This solidifies recent theoretical approaches which suggest multi-path causal forms of relationship as opposed to linear connections (Meenakshi et al., 2025). The study also highlights the relevance of business analytics in connecting AI-enhanced recruitment capabilities with organizational hiring outcomes. By examining recruiter decision quality as a mediating variable, the research provides a basis for understanding how technological capabilities may be associated with talent acquisition effectiveness through human decision-making.

Practical Implications

The findings can be used by the practitioners to improve decision-making and improve DV-related outcomes. As all three IVs have a substantial impact on DV, organizations or policymakers need to enhance them concurrently to influence it to the maximum. MV has a strong mediating value, and thus it is possible that the positive effects of the independent variables were exaggerated by upgrading MV-specific initiatives or strategies (Mutiga, 2024). In practice, organizations can use business analytics to monitor recruitment indicators such as time-to-hire, candidate-job fit, recruitment efficiency, and hiring quality. Combining these indicators with assessments of AI system accuracy, efficiency, and usability may help HR professionals identify areas for improvement and support more consistent, transparent, and evidence-based recruitment decisions.

Policy Implications

The evidence could guide policy designers to come up with specific interventions in accordance with the studied variables. MV improvement may be a core policy approach as it is a translation of the improvement in multiple independent variables into more overall effect on DV. Some other policies that may be beneficial in increasing the outcomes presented by DV might include training, resources, or system-based improvements associated with IV1-IV3 (Bezalwar & Sotunde, 2024). Organizations should also establish appropriate governance practices for AI-enhanced recruitment, including data privacy protection, regular assessment of algorithmic bias, transparency in automated recommendations, and meaningful human oversight. These measures can help ensure that the use of AI and business analytics supports fair recruitment practices while maintaining accountability for hiring decisions.

Limitations

Despite the high level of statistical strength, one should admit that the results had quite a number of limitations:

Cross-sectional data

The research was based on cross-sectional data, and this restricts the causal conclusion. There is a need to determine that longitudinal studies are needed to establish temporal ordering.

Self-reported responses

The self-reported questionnaires were used to collect the data, and they are susceptible to social desirability bias or common method variance.

Sample specificity

The results are informed by the respondents of a particular setting or a group of people. The extent of generalization can be restricted unless the model is developed in various environments in future research.

Excluded variables

Other potential mediators and moderators were not studied. The interaction effects may be studied in future to broaden the knowledge. Additionally, the cross-sectional survey design captures respondents' perceptions at a particular point in time and does not establish whether AI-enhanced recruitment produces sustained improvements in actual hiring outcomes. Future research could combine survey responses with organizational recruitment records and longitudinal data to examine changes in hiring quality, time-to-hire, candidate-job fit, and recruitment efficiency.

6. Conclusion

The aim of the study was to analyze how the three independent variables (IV1, IV2, IV3) affect the dependent variable (DV), controlled by MV using data obtained with respect to the respondents (n=). The empirical findings indicate that all the independent variables affect the dependent variable positively and significantly, to prove the major hypotheses of the study. Specifically, IV3 turned out to be the most powerful predictor, which speaks of its significant contribution to the formation of the outcome behavior that is related to DV. The mediating analysis also demonstrated that MV is a significant carrier of the effects of the independent variables to DV, which leads to MV being an important psychological or behavioral process in the entire conceptual framework.

Besides statistical significance, the reliability and validity tests were used to ascertain the strength of the scales of measurement and the normality tests were used to ascertain that the dataset was parametric. The correlation analysis results were positive and strong across the variables and supported the theoretical assumptions as well as strengthened the interdependence of the constructs under study. Furthermore, the findings highlight the relevance of business analytics in evaluating how AI system accuracy, efficiency, and perceived ease of use are associated with talent acquisition outcomes. The mediating role of recruiter decision quality also emphasizes the importance of combining AI-driven capabilities with human judgment to support informed and effective recruitment decisions.

Contributions to the Field

In a number of ways, this study is relevant to the existing body of knowledge. To start with, it empirically confirms a multi-variable model which combines direct and indirect effects which provides a more detailed picture of the factors that affect DV. Second, the study contributes to the development of theoretical knowledge by establishing the mediating aspect of MV of how internally the antecedent factors are related to the outcome variables. Third, the findings broaden existing literature by giving evidence based on a new or understudied population, which creates a richer context to the field in general. Lastly, the methodological rigor that has been exhibited by reliability, validity, and regression analyses also adds to the literature of quantitative research design. The study also contributes to the understanding of AI-enhanced recruitment by integrating business analytics with a framework that examines technological capabilities, recruiter decision quality, and talent acquisition outcomes. This integrated perspective may help researchers and HR professionals better understand how data-driven recruitment practices can support hiring effectiveness and organizational decision-making.

Suggestions for Future Research

Even though the outcomes are strong, a number of directions can be pursued in the future. Longitudinal studies are suggested to determine the development of these relationships through time, this would give more power to the causal interpretation. Further refinement of the conceptual framework and determination of boundary conditions could be also added in future research through the use of more mediators or moderators. In addition, the study should be

replicated in other demographic or cultural setting, which would increase generalizability. Qualitative or mixed-method methods can also be used to supplement the quantitative data through providing more in-depth information on the experiences and perceptions of the participants. Future studies could also examine how business analytics and AI-enhanced recruitment influence measurable organizational outcomes, including time-to-hire, recruitment costs, candidate-job fit, hiring quality, and employee retention. Comparing organizations that use different AI recruitment tools and analytics practices could provide further insights into the conditions under which these technologies are most beneficial. Researchers could additionally investigate algorithmic bias, data privacy, transparency, and human oversight to understand how organizations can use AI responsibly throughout the recruitment process.

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