

Analysis of the Effect of Skills-Based Hiring and AI Application in the Selection Process on Employee Turnover Intention

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Abstract

This study aims to analyze the effect of skills-based hiring on the use of AI in the selection process and employee turnover intention, as well as the effect of the use of AI in the selection process on employee turnover intention. The study employed a quantitative approach with 102 respondents selected using purposive sampling. Data were collected via a questionnaire using a 5-point Likert scale and analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with the assistance of SmartPLS 3.0. The results indicate that Skills-Based Hiring has a positive and significant effect on the use of AI in the selection process, with a path coefficient of 0.424, a t-statistic of 5.063, and a p-value of 0.000. Skills-Based Hiring also has a positive and significant effect on Employee Turnover Intention, with a path coefficient of 0.270, a t-statistic of 2.831, and a p-value of 0.00482. Furthermore, the use of AI in the selection process has a positive and significant effect on employee turnover intention, with a path coefficient of 0.466, a t-statistic of 5.178, and a p-value of 0.000. The R-Square value indicates that Skills-Based Hiring explains 18.0% of the variation in AI Application in the Selection Process, while Skills-Based Hiring and AI Application in the Selection Process together explain 39.6% of the variation in Employee Turnover Intention. These findings indicate a significant relationship between skills-based hiring approaches, the application of AI in the selection process, and employee turnover intention.

Keywords: skills-based hiring, artificial intelligence, turnover intention, SmartPLS 3.0, PLS SEM.

INTRODUCTION

Technological development and intensifying competition in the labor market have made human resources a key factor in organizational sustainability. High employee turnover intention can directly increase recruitment and training costs while also causing the loss of organizational knowledge. This issue is especially important in the technology sector, where workforce mobility tends to be relatively high.

To address this challenge, companies have begun adopting skills-based hiring to improve the alignment between employee capabilities and job requirements. This approach places greater emphasis on actual competencies rather than formal qualifications, which may in turn enhance occupational contentment as well as workforce loyalty. In addition, the

application of artificial intelligence throughout the recruitment screening process aims to strengthen evaluation efficiency together with assessment neutrality for candidates.

Although these approaches are increasingly being implemented, empirical studies examining the combined effect of skills-based hiring and AI implementation on employee turnover intention remain limited. Particularly in Indonesia's digital technology ecosystem.

Skill-Based Hiring

The indicators for the Skill-Based Hiring variable (X1) were developed by adapting the concept of skill-based hiring from Taamneh et al. (2026), which emphasizes skill evaluation, ability assessment, practical skills, and decision-making based on job-relevant competencies. In this study, the indicators used include:

1. Assessment of job-relevant skills
2. Use of skill tests or assessments
3. Consideration of experience and practical abilities
4. Ability assessment based on evidence of skills
5. Opportunities for applicants based on their skills

AI Applications in the Selection Process

The variable Application of Artificial Intelligence in Selection (X2) was developed by adapting the research by Putro and Siswanto (2025) on the use of AI in the recruitment and selection process. As well as that by Pratama et al. (2025) on the objectivity of AI in recruitment and selection. In this study, the indicators used include:

1. The use of AI technology in the selection process
2. Speed and efficiency of the selection process
3. Objective evaluation of candidates
4. Reduction of human bias
5. Accuracy in evaluating candidates

Turnover Intention

The Turnover Intention variable (Y) is adapted from the turnover intention construct used by Bothma and Roodt (2013), which includes the following indicators:

1. Considerations for leaving the job
2. Intention to leave the company
3. Consideration of alternative jobs
4. Tendency to leave the job
5. Desire to leave the company

Research Gap

1. Research on skills-based hiring continues to focus largely on employee retention, job satisfaction, candidate quality, and recruitment effectiveness. Pinto et al. (2025), found that skills-based hiring is associated with employee retention and job satisfaction, but they have not specifically examined employee turnover intention as a dependent variable.
2. Research on artificial intelligence in human resource management has also begun to examine its relationship with turnover intention. Moin and Zhang (2025), as well as Wang

and He (2026), demonstrated a correlation between the use or adoption of AI and turnover intention. However, research that specifically examines the application of AI in the selection process in relation to employee turnover intention remains limited.

3. Research that integrates skills-based hiring and the application of artificial intelligence in the selection process into a single research model remains limited. Therefore, this study fills this research gap by examining the effects of skills-based hiring and the application of artificial intelligence in the selection process on employee turnover intention.

Research Novelty

1. This study integrates Skills-Based Hiring and the application of Artificial Intelligence in the selection process into a single research model.
2. This study uses Employee Turnover Intention as the dependent variable to examine its relationship with changes in recruitment practices and the use of technology in the selection process.
3. This study also examines the relationship between Skills-Based Hiring and the application of Artificial Intelligence in the selection process. thereby providing insights into the connection between a skills-based hiring approach and the use of AI technology.
4. This research model makes an empirical contribution to the field of human resource management by integrating a skills-based hiring. AI technology in recruitment. and employee turnover intention into a single research framework.

METHOD

Research Population and Sample

The population in this study consists of employees working at companies that implement a skills-based hiring and selection process and use artificial intelligence in the selection process. Sampling was conducted using a nonprobability sampling approach. Specifically, purposive sampling, with the following respondent criteria:

1. Employees who are currently active at their place of employment
2. Have been employed for at least 6 months
3. Have participated in the recruitment and selection process at their current company

The number of respondents in this study was 102. All of whom were deemed to have met the minimum criteria for Partial Least Squares Structural Equation Modeling (PLS-SEM) analysis. In which the sample size can be adjusted according to the model's complexity (Hair et al., 2017).

Data Collection Method

Research data were collected using a questionnaire designed based on the indicators of each variable. The questionnaire was distributed online to respondents to facilitate access and improve the efficiency of data collection. The research instrument used a 5-point Likert scale. with the following rating ranges: 1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree.

Data Analysis Techniques

The data analysis technique used in this study was Partial Least Squares (PLS)-based Structural Equation Modeling (SEM), conducted using SmartPLS 3.0 software. The PLS-SEM method was chosen because it can analyze complex models with a relatively small sample size and does not require a normal data distribution (Hair et al., 2017). The analysis was conducted in two main stages. namely:

1. Evaluation of the Measurement Model (Outer Model)

This evaluation aims to test the validity and reliability of the constructs, which include:

- Convergent Validity: assessed based on outer loading values (>0.70) and Average Variance Extracted (AVE >0.50).
- Discriminant Validity: assessed using cross-loadings and the HTMT value (<0.90).
- Reliability: measured using Cronbach's Alpha and Composite Reliability (>0.70).

2. Structural Model Evaluation (Inner Model)

This evaluation aims to test the relationships among variables, which include:

- Multicollinearity Test: using the VIF value (<5).
- Coefficient of Determination (R^2): to assess the ability of the independent variables to explain the dependent variable.
- Effect Size (f^2): to measure the magnitude of each variable's effect.
- Predictive Relevance (Q^2): to assess the model's predictive ability.
- Hypothesis Testing: using the bootstrapping method with criteria of a t-statistic > 1.96 and a p-value < 0.05 .

Research Model

Conceptually, this research model can be simply described as follows:

1. Skill-Based Recruitment (X1) $\rightarrow$ AI Application in the Selection Process (X2)
2. Skill-Based Recruitment (X1) $\rightarrow$ Turnover Intention (Y)
3. AI Application in the Selection Process (X2) $\rightarrow$ Turnover Intention (Y).

RESULT AND DISCUSSION

Research Results and Analysis

The data for this study were collected through a questionnaire survey involving 102 respondents. Respondent characteristics were classified by gender, age, employment status, and length of employment. The data details are presented in Table 1.

Table 1. Respondent Characteristics

Characteristics	Category	Number	Percentage
Gender	Male	45	44.1%
	Female	57	55.9%
Total		102	100%
Age	< 20 years old	14	13.7%
	20–22 years old	47	46.1%
	23–25 years old	22	21.6%
	> 25 years old	19	18.6%
Total		102	100%
Length of Employment	1–3 years	35	34.3%
	4–6 years	62	60.8%
	> 6 years	5	4.9%
Total		102	100%

Source: Data Processed by the Researcher (2025)

Analysis of the Measurement Model (Outer Model)

Convergent Validity Test Results

Convergent validity is used to determine the extent to which indicators are able to represent the construct being measured. The test is conducted by examining the outer loading and Average Variance Extracted (AVE) values. In PLS-SEM analysis, a higher outer loading value indicates that the indicators are better able to reflect the research construct. While an AVE value above 0.50 indicates that the construct is able to explain more than 50% of the variance in its indicators. The results of the outer loading calculations in the convergent validity test can be seen in Table 2, Table 3, and Figure 1.

Table 2. Outer Loading

Variable	Indicator	Item	Outer Loading	Validity
Skill-Based Recruitment (X1)	Assessment of job-relevant skills	X1-1	0.754	Valid
	Use of skill tests or assessments	X1-2	0.845	Valid
	Consideration of experience and practical skills	X1-3	0.777	Valid
	Assessment of competence based on evidence of skills	X1-4	0.812	Valid
	Opportunities for applicants based on their skills	X1-5	0.706	Valid
AI Application in the Selection Process (X2)	Use of AI technology in the selection process	X2-1	0.793	Valid
	Speed and efficiency of the selection process	X2-2	0.865	Valid
	Objective evaluation of candidates	X2-3	0.923	Valid
	Reduction of human bias	X2-4	0.871	Valid
	Accuracy in evaluating candidates	X2-5	0.850	Valid
Turnover Intention (Y)	Reasons for leaving a job	Y1	0.882	Valid
	Intention to leave the company	Y2	0.888	Valid
	Consideration of alternative jobs	Y3	0.873	Valid
	Desire to leave the company	Y4	0.868	Valid
	Reasons for leaving a job	Y5	0.835	Valid

Source: SmartPLS 3.0 Output, Processed Primary Data (2025)

Based on the results of data processing using SmartPLS. All indicators in the Skills-Based Hiring variable have outer loadings ranging from 0.706 to 0.845. These values indicate that all indicators meet the criteria for convergent validity because they are above the 0.70 threshold. For the AI Application in the Selection Process variable. The outer loading values range from

0.793 to 0.923. All indicators have values above 0.70 and can therefore be considered to meet the criteria for convergent validity. Meanwhile, the Employee Turnover Intention variable has outer loading values ranging from 0.835 to 0.888.

All indicators also have values above 0.70. All indicators for the three research variables have met the criteria for convergent validity and can be used in further analysis.

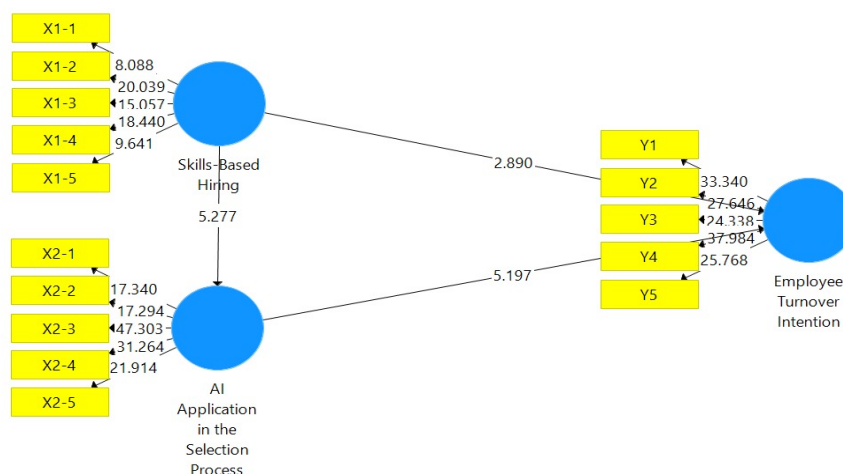


Figure 1. Outer Loading

Source: SmartPLS 3.0 Output, Processed Primary Data (2025)

Table 3. Average Variance Extracted (AVE)

Variable	Average Variance Extracted (AVE)
Skill-Based Recruitment (X1)	0.609
AI Application in the Selection Process (X2)	0.742
Turnover Intention (Y)	0.756

Source: SmartPLS 3.0 Output, Processed Primary Data (2025)

The AVE test results show that the AVE value for Skills-Based Hiring is 0.609, for AI Application in the Selection Process is 0.742, and for Employee Turnover Intention is 0.756. All of these values are above the minimum threshold of 0.50. Each construct is able to explain more than 50% of the variance in its respective indicator. These results indicate that the three constructs in this study have met the criteria for convergent validity.

Discriminant Validity Test Results

Discriminant validity aims to ensure that each construct in the study has distinct characteristics and that there is no overlap in measurement between variables. Discriminant validity was tested in this study using cross-loading values and the Heterotrait-Monotrait Ratio (HTMT). The results of the calculations for the discriminant validity test are presented in Table 4 and Table 5.

Table 4. Cross-Loading

Item	Skill-Based Recruitment (X1)	AI Application in the Selection Process (X2)	Turnover Intention (Y)
X1-1	0.754	0.271	0.381
X1-2	0.845	0.387	0.354
X1-3	0.777	0.385	0.381
X1-4	0.812	0.327	0.365
X1-5	0.706	0.267	0.342
X2-1	0.408	0.793	0.572
X2-2	0.391	0.865	0.492
X2-3	0.400	0.923	0.492
X2-4	0.371	0.871	0.462
X2-5	0.214	0.850	0.454
Y1	0.455	0.463	0.882
Y2	0.372	0.430	0.888
Y3	0.302	0.454	0.873
Y4	0.447	0.627	0.868
Y5	0.426	0.504	0.835

Source: SmartPLS 3.0 Output, Processed Primary Data (2025)

Based on the cross-loading results, each indicator has the highest loading value for the construct it measures compared to its loading values for other constructs. This indicates that the Skills-Based Hiring indicator more strongly represents the Skills-Based Hiring construct. The AI Application in the Selection Process indicator more strongly represents the AI Application in the Selection Process construct. And the Employee Turnover Intention indicator more strongly represents the Employee Turnover Intention construct.

Table 5. Heterotrait-Monotrait Ratio (HTMT)

Variable	Skills-Based Hiring (X1)	AI Application in the Selection Process (X2)	Turnover Intention (Y)
Skills-Based Hiring (X1)			
AI Application in the Selection Process (X2)	0.469		
Turnover Intention (Y)	0.525	0.616	

Source: SmartPLS 3.0 Output, Processed Primary Data (2025)

The HTMT test results showed a value of 0.469 between Skills-Based Hiring and AI Application in the Selection Process. 0.525 between Skills-Based Hiring and Employee Turnover Intention. And 0.616 between AI Application in the Selection Process and Employee Turnover Intention. All of these values are below the 0.90 threshold. The discriminant validity of the research model has been met.

Reliability Test Results

Reliability tests were conducted to determine the consistency of the indicators in measuring the research constructs. Reliability can be assessed through Cronbach's Alpha, rho_A, and Composite Reliability. A construct is considered reliable if the Composite Reliability value exceeds 0.70. In accordance with the criteria proposed by Sarwono and Narimawati (2015) and Ghazali and Latan (2015).

Table 6. Composite Reliability and Validity

Variable	Cronbach's Alpha	rho_A	Composite Reliability
Skill-Based Recruitment (X1)	0.838	0.843	0.886
AI Application in the Selection Process (X2)	0.913	0.918	0.935
Turnover Intention (Y)	0.920	0.929	0.939

Source: SmartPLS 3.0 Output, Processed Primary Data (2025)

The data analysis results show that Skills-Based Hiring has a Cronbach's Alpha value of 0.838. A rho_A value of 0.843, and a Composite Reliability of 0.886. AI Application in the Selection Process has a Cronbach's Alpha value of 0.913. A rho_A value of 0.918. And a Composite Reliability of 0.935. Meanwhile, Employee Turnover Intention has a Cronbach's Alpha of 0.920. A rho_A of 0.929, and a Composite Reliability of 0.939.

All Cronbach's Alpha and Composite Reliability values are above 0.70. All research constructs are deemed reliable and possess good internal consistency, making them suitable for structural equation modeling.

Structural Model Analysis (Inner Model)

Multicollinearity Test Results

According to Hair et al. (2017) a low VIF value (below 5) indicates that each independent variable makes a distinct contribution to explaining the dependent variable. Without overlapping. Next, the analysis focuses on the VIF values presented in Table 7.

Table 7. Variance Inflation Factor (VIF)

Variable	Skill-Based Recruitment (X1)	AI Application in the Selection Process (X2)	Turnover Intention (Y)
Skill-Based Recruitment (X1)		1.000	1.219
AI Application in the Selection Process (X2)			1.219
Turnover Intention (Y)			

Source: SmartPLS 3.0 Output, Processed Primary Data (2025)

Based on the SmartPLS analysis results. The VIF value for the relationship between Skills-Based Hiring and AI Application in the Selection Process is 1.000. While the VIF value for the constructs influencing Employee Turnover Intention is 1.219. All of these values are below the threshold of 5.

The research model does not indicate the presence of multicollinearity. This suggests that the independent variables in the model make distinct contributions to explaining the endogenous variable.

Results of the Coefficient of Determination Test

The R-squared test measures the ability of exogenous variables to explain the endogenous variable in the model. The R-squared values are presented in Table 8.

Table 8. R-Square

Variable	R-Square	Adjusted R-Square
AI Application in the Selection Process (X2)	0.180	0.172
Turnover Intention (Y)	0.396	0.384

Source: SmartPLS 3.0 Output, Processed Primary Data (2025)

The test results show that the R-Square value for AI Application in the Selection Process is 0.180. With an Adjusted R-Square value of 0.172. This means that Skills-Based Hiring explains 18.0% of the variation in AI Application in the Selection Process. While the remaining 82.0% is explained by other factors not included in the research model.

The R-Square value for Employee Turnover Intention was 0.396. with an Adjusted R-Square value of 0.384. This means that Skills-Based Hiring and the Application of AI- s in the Selection Process together account for 39.6% of the variation in Employee Turnover Intention. While the remaining 60.4% is explained by other factors outside the research model.

These results indicate that the research model is capable of explaining the variation in Employee Turnover Intention through Skills-Based Hiring and the use of AI in the selection process.

Effect Size Test Results

The f-square value indicates how strong the influence of a variable is in explaining changes in another variable. According to Juliandi. A (2018), an f-square value of 0.02 is categorized as a small effect. 0.15 as a moderate effect. and 0.35 as a large effect. The f-square values are presented in Table 9.

Table 9. F-Square

Variable	X1	X2	Y
Skill-Based Recruitment (X1)		0.219	0.099
AI Application in the Selection Process (X2)			0.295
Turnover Intention (Y)			

Source: SmartPLS 3.0 Output, Processed Primary Data (2025)

Based on the data analysis results. the f-square value for Skills-Based Hiring on AI Application in the Selection Process is 0.219. This value indicates a moderate effect. The f-Square value for Skills-Based Hiring on Employee Turnover Intention is 0.099. This value indicates a relatively small effect. Meanwhile, the f-Square value for the relationship between AI Application in the Selection Process and Employee Turnover Intention is 0.295. This value indicates a moderate effect.

Based on the f-Square values, the relationship between the use of AI in the selection process and employee turnover intention has a greater effect than the direct relationship between skills-based hiring and employee turnover intention.

Predictive Relevance Test Results

Q-Square is used to assess a model's predictive ability in explaining observed data. A Q-Square value greater than 0 indicates that the model has predictive relevance, meaning it is capable of accurately predicting the endogenous variable. The Q-Square values are presented in Table 10.

Table 10. Q-Square

Variable	SSO	SSE	Q ² (=1-SSE/SSO)
AI Application in the Selection Process (X2)	510.000	447.168	0.123
Turnover Intention (Y)	510.000	365.419	0.283
Skill-Based Recruitment (X1)	510.000	510.000	

Source: SmartPLS 3.0 Output, Processed Primary Data (2025)

The analysis results show that the Q-Square value for AI Application in the Selection Process is 0.123. while the Q-Square value for Employee Turnover Intention is 0.283. Both values are above 0. The research model has predictive relevance in explaining the variables AI Application in the Selection Process and Employee Turnover Intention.

Hypothesis Testing

Hypothesis testing was conducted using the bootstrapping method in SmartPLS. The test was performed by examining the original sample values or path coefficients, t-statistics, and p-values. A hypothesis was considered to have a significant effect if the t-statistic was greater than 1.96 and the p-value was less than 0.05.

Table 11. Path Coefficients

Variable	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T-Statistics (O/STDEV)	P-Values
Skill-Based Recruitment (X1) → AI Application in the Selection Process (X2)	0.424	0.432	0.084	5.063	0.000
Skill-Based Recruitment (X1) → Turnover Intention (Y)	0.270	0.277	0.095	2.831	0.005
AI Application in the Selection Process (X2) → Turnover Intention (Y)	0.466	0.462	0.090	5.178	0.000

Source: SmartPLS 3.0 Output, Processed Primary Data (2025)

Hypothesis 1

The effect of Skills-Based Hiring on AI Application in the Selection Process shows a path coefficient of 0.424, this value has a positive direction. The bootstrapping results show a t-statistic of 5.063 and a p-value of 0.000. The t-statistic is greater than 1.96 and the p-value is less than 0.05. These results indicate that Skills-Based Hiring has a positive and significant effect on the Application of AI in the Selection Process. This means that changes in the implementation of Skills-Based Hiring in the research model are followed by positive changes in the Application of AI in the Selection Process. Hypothesis 1 is accepted.

Hypothesis 2

The effect of Skills-Based Hiring on Employee Turnover Intention shows a path coefficient of 0.270. This value indicates a positive relationship. The test results show a t-statistic of 2.831 and a p-value of 0.005. The t-statistic is greater than 1.96, and the p-value is less than 0.05. The results indicate that skills-based hiring has a positive and significant effect on employee turnover intention. There is a significant relationship between skills-based hiring and employee turnover intention in the research model. Hypothesis 2 is accepted.

Hypothesis 3

The effect of AI Application in the Selection Process on Employee Turnover Intention shows a path coefficient of 0.466, this value has a positive direction. The bootstrapping results show a t-statistic of 5.178 and a p-value of 0.000. The t-statistic is greater than 1.96 and the p-value is less than 0.05. These results indicate that the use of AI in the selection process has a positive and significant effect on employee turnover intention. Hypothesis 3 is accepted.

Discussion and Implications of the Results

The Impact of Skills-Based Hiring on the Use of AI in the Selection Process

The results of the hypothesis testing show that Skills-Based Hiring has a positive and significant effect on the Application of AI in the Selection Process. with a path coefficient of 0.424, a t-statistic of 5.063, and a p-value of 0.000. These findings indicate that the stronger the implementation of a skills-based hiring approach within an organization. The higher the level of artificial intelligence utilization in the employee selection process.

These findings are consistent with the results of a study by Bone et al. (2025), who through an analysis of approximately 11 million job postings in the United Kingdom from 2018 to mid-2024. Found a significant increase in the adoption of skills-based hiring, particularly for jobs related to AI. The consistency of these findings is also supported by Dadaboyev et al. (2025), who demonstrated that AI is widely used for automated resume parsing, candidate screening, and predictive analytics in the recruitment process. An organization's focus on candidates' skills tends to go hand in hand with the adoption of technology to identify and match those competencies.

The Impact of Skills-Based Hiring on Employee Turnover Intention

The test results show that skills-based hiring has a positive and significant effect on employee turnover intention, with a path coefficient of 0.270, a t-statistic of 2.831, and a p-value of 0.005. This means that an increase in the implementation of skills-based hiring. In the context of this study, is associated with an increase in employees' tendency to change jobs.

These findings should be interpreted contextually, taking into account the characteristics of the organization and how they are implemented in practice. The adoption of skills-based hiring tends to increase the visibility of and recognition for the specific skills that employees possess. As certain skills become more valuable in the labor market, employees with those competencies may have more external opportunities. which could theoretically encourage them to consider changing jobs.

This argument is supported by the findings of Bone et al. (2025), which reveal that companies are increasingly relying on skills-based hiring to expand their talent pool and meet evolving skill needs, and that there is a wage premium of approximately 23% for AI skills in the jobs studied. This phenomenon also helps explain why possessing certain skills confers greater bargaining power in the labor market, which in turn can influence employees' intentions to stay or leave.

The Impact of AI Application in the Selection Process on Employee Turnover Intention

The results of the analysis show that the use of AI in the selection process has a positive and significant effect on employee turnover intention, with a path coefficient of 0.466, a t-statistic of 5.178, and a p-value of 0.000. This path coefficient (0.466) is greater than the path coefficient of Skills-Based Hiring on Employee Turnover Intention (0.270), indicating that in this research model, the application of AI in the selection process has a stronger relationship with turnover intention than the direct effect of Skills-Based Hiring.

Dadaboyev et al. (2025) explain that AI can improve the efficiency of the recruitment process through resume screening, candidate matching, automated assessment, and automatic analysis of candidate profiles. However, on the other hand, the implementation of AI also raises a number of issues, such as process transparency, potential algorithmic bias, and the need for human oversight. Chen et al. (2025), found that the level of transparency regarding AI use in the recruitment process can influence candidates' perceptions of person-job fit. While Babaee and Shank (2025) emphasize the importance of trust and procedural justice in the context of AI-driven hiring.

Theoretical Implications of the Research Findings

This study contributes to the development of human resource management research by integrating three variables: skills-based hiring, the application of AI in the selection process, and employee turnover intention. The finding that Skills-Based Hiring is positively associated with the application of AI in the selection process reinforces the theoretical understanding that a skills-based hiring approach fundamentally requires a systematic mechanism for identifying and matching competencies, in which AI technology can serve as an enabler in that process.

Practical Implications

For organizations, the findings of this study underscore the importance of establishing skill and competency standards that are relevant to the requirements of each position. As well as periodically updating those standards in line with evolving job needs. When applying AI to the selection process, organizations must prioritize transparency, accuracy, consistency, and human oversight to ensure that the technology supports an ethical and responsible selection process.

Organizations are advised to transparently communicate the purpose of using AI, explain the role of technology in the selection process, and provide training and skill-development programs for employees. These steps are expected to help employees understand the changing competency requirements and adapt to the organization's direction. Thereby potentially minimizing turnover intentions arising from concerns about technological change.

Limitations of the Study

This study has several limitations that must be considered when interpreting its results. First, the study employed a cross-sectional design with data collected at a single point in time; therefore, it cannot explain the dynamics of changes in employee turnover intention over the long term or establish temporal causal relationships. Second, the use of purposive sampling with specific respondent characteristics limits the generalizability of the study's findings to employee populations or industrial sectors with different characteristics. Third, this study included only Skills-Based Hiring and AI Application in the Selection Process as independent variables. The relatively small f-square value for Skills-Based Hiring regarding Employee Turnover Intention (0.099) indicates the presence of other factors that also explain the variance

in turnover intention which have not been included in this study's model.

Fourth, the measurement of variables in this study relies on questionnaires based on respondents' perceptions. Specifically, regarding the AI Application in the Selection Process variable, differences in respondents' levels of understanding of AI technology and the extent to which AI is applied in the selection process have the potential to affect the consistency of the ratings provided.

Fifth, this study focuses on the application of AI in the selection process in general. Without distinguishing in depth between the types or levels of its use, such as AI for resume screening, candidate matching, automated assessment, chatbots, or AI-based interviews. Future research is recommended to identify more specific types of AI usage in order to examine their respective effects on Employee Turnover Intention more precisely.

CONCLUSION

Based on the results of the study involving 102 respondents and the analysis using PLS-SEM, it can be concluded that:

1. Skills-Based Hiring has a positive and significant effect on the Application of AI in the Selection Process. This is evidenced by a path coefficient of 0.424, a t-statistic of 5.063, and a p-value of 0.000. This means that the more strongly skills-based hiring is implemented, the higher the application of AI in the selection process.
2. Skills-Based Hiring has a positive and significant effect on Employee Turnover Intention. The test results show a path coefficient of 0.270, a t-statistic of 2.831, and a p-value of 0.00482. An increase in the implementation of Skills-Based Hiring in the context of this study is followed by an increase in employee turnover intention.
3. The application of AI in the selection process has a positive and significant effect on employee turnover intention, with a path coefficient of 0.466, a t-statistic of 5.178, and a p-value of 0.000. These values indicate that the relationship between the application of AI in the selection process and turnover intention is stronger than the direct effect of skills-based hiring on turnover intention.
4. Skills-Based Hiring and the Use of AI in the Selection Process account for 39.6% of the variation in Employee Turnover Intention. While the remaining 60.4% is explained by other factors outside the research model. Additionally, Skills-Based Hiring accounts for 18.0% of the variation in the Use of AI in the Selection Process.

Recommendations

Based on the research findings and existing limitations, the following recommendations can be offered: For companies, the implementation of Skills-Based Hiring should be carried out by establishing clear and relevant skill and competency standards for each position and updating them periodically. For future researchers, it is recommended to include other variables that may influence Employee Turnover Intention, such as job satisfaction, career development, perceived organizational support, employee engagement, person-job fit, and compensation.

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