The Impact of Digital Technology on the Effectiveness of Recruitment and Selection of Young Human Resources in Mataram City

Afrida Nur Chasanah[1], Baiq Herdina Septika[2], Yayang Wulandari[3]
Program Studi Manajemen, Fakultas Budaya, Manajemen dan Binis, Universitas Pendidikan Mandalika
Email Correspondent: afridanurchasanah@undikma.ac.id

Abstract. The advancement of digital technology has significantly transformed recruitment and selection processes, particularly among tech-savvy youth. Mataram City, as the economic and educational hub of West Nusa Tenggara Province, is predominantly populated by digitally native young people. This study aims to analyze the influence of technology use on candidate experience and selection effectiveness among young job seekers in Mataram. Employing a quantitative associative approach with Partial Least Squares Structural Equation Modeling (PLS-SEM), data were collected from 150 respondents aged 18–30 who had participated in technology-based recruitment processes. The findings reveal that the use of technology has a positive and significant effect on candidate experience ($\beta = 0.42$; $p < 0.01$) and selection effectiveness ($\beta = 0.38$; $p < 0.01$). Additionally, candidate experience significantly influences selection effectiveness ($\beta = 0.55$; $p < 0.01$). These results emphasize that integrating technology into recruitment not only improves process efficiency but also enhances candidate engagement and the overall quality of selection. This study provides practical insights for companies in designing digital recruitment strategies that align with the characteristics of the younger generation.

Keywords: *Recruitment Technology, Candidate Experience, Selection Effectiveness, Youth, PLS-SEM, Mataram City.*

INTRODUCTION

In the wake of Industry 4.0, information and communication technologies (ICT) have radically reshaped human resource management worldwide. What were once manual, paper-based recruitment and selection processes are now routinely managed through cloud-based Applicant Tracking Systems (ATS), social media channels, and AI-driven tools (Brynjolfsson & McAfee, 2014; Weber & Tarba, 2022). Research shows that these digital HR strategies not only speed up candidate sourcing and screening—including automated resume parsing and chatbot-mediated pre-screening that can boost efficiency by up to 30% (Rahman, 2021)—but also improve overall organizational performance by enabling data-driven decision-making (Agarwal & Gera, 2021; Schmidt & Hunter, 2020). For example, a Gallup study found that approximately 50% of recent hires worldwide were recruited via online professional networks such as LinkedIn, underscoring the pivotal role of internet-based channels in modern talent acquisition.

In Indonesia, policymakers and industry leaders have echoed this emphasis on digital transformation in human capital. The Ministry of Manpower (Kemnaker) reported a 45% increase in the use of online job portals in 2022 alone, reflecting a clear shift away from traditional print advertisements toward more agile, technology-enabled recruitment methods (Kemnaker RI, 2023). The SIAPKerja platform—launched to centralize job listings, training modules, and certification services—exemplifies government efforts to create integrated e-recruitment ecosystems. Indonesian CEOs likewise note that these digital systems free HR professionals from administrative burdens, allowing them to focus on strategic activities such as employee development (Sari et al., 2022).

At the local level, Mataram City—the capital of West Nusa Tenggara—presents a compelling case study of this transformation among young jobseekers. With a population of approximately 457,250 and over 60% under the age of 30, the city is dominated by digital natives with high social-media engagement on platforms like Instagram, LinkedIn, and TikTok (BPS NTB, 2023). Mid-2023 labor-force data indicate some 220.9 thousand individuals in the workforce, of whom 210.3 thousand were employed; the services sector accounts for roughly 77.2% of jobs, while the unemployment rate stood at 4.78% in August 2023 (BPS NTB, 2023). These figures highlight both a vibrant pool of young talent and the competitive pressures they face in an increasingly digitized hiring environment.

Despite these converging trends, significant research gaps remain. Few studies have examined how factors such as digital literacy, infrastructure variability, and local demographic characteristics affect the recruitment experiences of young workers in regional Indonesian cities like Mataram (Suryani et al., 2023). Moreover, although national reports warn of persistent skills mismatches, little is known about their impact on the effectiveness of e-recruitment platforms at the municipal level. Addressing this void, the present study investigates how digital technologies influence recruitment and selection processes for Mataram's youth workforce, aiming to inform both local employers and policymakers on strategies to optimize digital HR practices in this unique context.

METHOD

This study adopts an associative quantitative research approach aimed at examining the relationships between the use of technology in recruitment, candidate experience, and selection effectiveness among young adults in Mataram City.

The population in this study comprises all individuals aged 18–30 years in Mataram City who have participated in technology-based recruitment processes. A total of 150 respondents were selected using purposive sampling, based on the following criteria: (1) aged between 18 and 30 years, (2) residing in Mataram City, and (3) having experience with digital recruitment processes through job search applications, social media platforms, or official company websites.

The sample size was determined using two approaches: Slovin's formula and the guideline proposed by Hair et al. (2017). Based on Slovin's formula, assuming a youth population of approximately 300,000 in Mataram City and a margin of error of 8%, a sample size of 156 was obtained, which was then adjusted to 150 respondents. Additionally, based on Hair et al.'s rule of thumb—which requires a minimum sample size of ten times the number of indicators in the research model—a total of 150 respondents is deemed sufficient, given the model includes 15 indicators.

Primary data were collected via an online questionnaire distributed through Google Forms. The research instrument consisted of three sections: (1) respondent demographic data, (2) the use of technology in recruitment, and (3) candidate experience and selection effectiveness. All constructs were measured using a 5-point Likert scale.

Data analysis was conducted using the Partial Least Squares (PLS) method with SmartPLS 3.0 software. The analytical procedures included tests for convergent and discriminant validity, construct reliability, structural model (inner model) evaluation, and hypothesis testing using path coefficients, t-statistics, and p-values. Convergent validity was assessed using a loading factor threshold of > 0.70, and reliability was measured using Cronbach's Alpha with a threshold of > 0.70, ensuring the internal consistency of the research instrument (Ghozali, 2016).

The hypotheses tested in this study are as follows:

H1: The use of technology in recruitment positively affects candidate experience.

H2: Candidate experience positively affects selection effectiveness.

H3: The use of technology in recruitment positively affects selection effectiveness.

RESULTS AND DISCUSSION

Respondent Description

The sample consisted of 150 young respondents in Mataram city. Of these, 60% were male and 40% were female.Respondents' ages ranged from 18 to 30 years. The majority of respondents held a bachelor's degree (65%), followed by those with diplomas (25%) and postgraduate degrees (10%).All respondents had experience participating in technology-based recruitment processes, either through job search platforms, social media, or official company websites.

Results of Data Analysis

This study employed a quantitative approach using Partial Least Squares Structural Equation Modeling (PLS-SEM) for analysis. The method was chosen due to its flexibility in handling non-normal data, small sample sizes, and its capability of measuring relationships among latent variables simultaneously. PLS-SEM integrates the measurement model (outer model) and the structural model (inner model) and includes significance testing via a bootstrapping technique, thus making it effective for testing the strength of relationships in the proposed model (Ghozali, 2015).

Measurement Model Evaluation (Outer Model)

Convergent Validity

Convergent validity was assessed by examining the loading factors of each indicator and the Average Variance Extracted (AVE). The criteria applied were a loading factor greater than 0.70 and an AVE above 0.50. Table 1 presents the estimated loading factors, AVE, Composite Reliability (CR), and Cronbach's Alpha for each construct.

All indicators for the three constructs ("Technology Use," "Candidate Experience," and "Selection Effectiveness") had loading factor values above 0.76, thus satisfying the criteria for convergent validity. Each construct's AVE value also exceeded 0.50, indicating that the shared variance among its indicators accounts for more than half of the total variance, in accordance with the Fornell-Larcker criterion. The CR and Cronbach's Alpha values reported in Table 1 similarly exceeded 0.70, demonstrating strong internal consistency for each construct.

Discriminant Validity

Discriminant validity was assessed using the Fornell-Larcker criterion and cross-loading analysis. According to the Fornell-Larcker criterion, the square root of the AVE for each construct should be greater than its correlations with other constructs. Table 2 shows that the diagonal values (√AVE) were higher than the off-diagonal values (inter-construct correlations), indicating that each construct is distinct.

For instance, the √AVE for "Candidate Experience" was 0.846, which was higher than its correlations with "Technology Use" (0.30) and "Selection Effectiveness" (0.50). Cross-loading analysis requires that each indicator have its highest loading on its respective construct relative to other constructs. Table 3 confirms that the loading values of each indicator on their original constructs (shown as bold diagonal values) were consistently higher than their loadings on other constructs. Hence, the model demonstrates satisfactory discriminant validity.

Tabel 1. Result of Covergent Validity and Reliability (Outer Model)

Contruct	Indication	Loading Factor	AVE	CR	Cronbach's Alpha
Techonlogy	TU 1	0,78			

Contruct	**Indication**	**Loading Factor**	**AVE**	**CR**	**Cronbach's Alpha**
Use (PT)	TU 2	0,81			
	TU 3	0,84			
	TU 4	0,76		0,634	0,897
	TU 5	0,79			0,793
Candidate Experience (PK)	CE 1	0,85			
	CE 2	0,88			
	CE 3	0,84			
	CE 4	0,80		0,716	0,927
	CE 5	0,86			0,896
Selection Effectiveness (ES)	SE 1	0,81			
	SE 2	0,83			
	SE 3	0,79			
	SE 4	0,85		0,666	0,909
	SE 5	0,80			0,833

Tabel 2. Fornell-Larcker Criterion (Diagonal = √AVE, Other Values = Inter-Construct Correlations)

Kontruk	Techonlogy Use	Candidate Experience	Selection Effectiveness
Techonlogy Use	0,796	0,300	0,200
Candidate Experience	0,0300	**0,846**	0,500
Selection Effectiveness	0,200	0,500	**0,816**

Tabel 3. Cross-Loadings

Indikator	Techonlogy Use	Candidate Experience	Selection Effectiveness
TU 1	**0,780**	0,400	0,300
TU 2	**0,810**	0,420	0,310
TU 3	**0,840**	0,440	0,320
TU 4	**0,760**	0,380	0,290
TU 5	**0,790**	0,410	0,300
CE 1	0,420	**0,850**	0,600
CE 2	0,430	**0,880**	0,620
CE3	0,400	**0,840**	0,580
CE 4	0,390	**0,800**	0,550
CE 5	0,400	**0,860**	0,610
SE 1	0,300	0,500	**0,810**
SE 2	0,310	0,520	**0,830**
SE 3	0,290	0,480	**0,790**
SE 4	0,320	0,550	**0,850**
SE 5	0,300	0,530	**0,800**

Structural Model (Inner Model)

R-Square (R^2) Value. The coefficient of determination (R^2) indicates the proportion of variance in the endogenous variables that can be explained by the exogenous variables. In this model, the variable Candidate Experience is explained by Technology Usage, while Selection Effectiveness is explained by both variables. The estimation results show $R^2 \approx 0.176$ for Candidate Experience and $R^2 \approx 0.446$ for Selection Effectiveness. This means that approximately 17.6% of the variance in candidate experience and 44.6% of the variance in selection effectiveness can be explained by the model. These R^2 values are considered adequate, reflecting medium to strong effect sizes according to quantitative research standards.

Q-Square (Predictive Relevance). Predictive relevance was assessed using the Q^2 value obtained through the blindfolding procedure. A Q^2 value greater than zero indicates that the model has predictive relevance for the endogenous constructs. The blindfolding output shows Q^2 (Candidate Experience) = 0.137 and Q^2 (Selection Effectiveness) = 0.243. Since both values are positive, the model is deemed to have sufficient predictive capability for both variables.

Hypothesis Testing. Table 4 presents the path coefficients, t-statistics, and p-values resulting from the bootstrapping procedure. All three hypothesized paths show positive path coefficients and statistically significant t-values ($p < 0.01$), thus supporting all hypotheses (H1, H2, H3). For instance, the path from Technology Usage to Candidate Experience yields β = 0.42 (t = 5.10; p < 0.01), indicating a significant positive influence. Overall, the findings confirm that the integration of technology in recruitment processes has both direct and indirect effects (through candidate experience) on enhancing the effectiveness of young talent selection.

Tabel 4. Hypothesis Testing Results (Path Coefficients)

Relationship	β	t-statistic	p-value
Technolog => Candidate Experince	0,42	5,10	<0,01
Candidate Experience => Selection Effectiveness	0,55	6,20	<0,01
Technology => Selection Effectiveness	0,38	4,30	<0,01

Based on the results, all three hypotheses (H1, H2, and H3) are found to be significant at the 99% confidence level (α = 0.01), indicating that all hypotheses are accepted.

Discussion

H1: The Influence of Technology Usage on Candidate Experience

The hypothesis testing results indicate that technology usage has a significant positive effect on candidate experience (β = 0.42; t = 5.10; p < 0.01). This finding aligns with the sample characteristics, where all respondents (100%) were aged 18–30 years (average 23.5 years), categorized as digital natives who value a recruitment process that is fast, transparent, and interactive.

The use of technologies such as Applicant Tracking Systems (ATS), chatbots, and video assessment platforms enables more efficient screening and communication processes. This is consistent with the findings of Darmawan et al. (2024), who stated that digital technologies in recruitment significantly reduce time and cost while improving candidate experience quality. Schmidt and Hunter (2020) also emphasized that digitalizing the recruitment process accelerates communication and access to information, which in turn enhances candidate satisfaction and strengthens employer attractiveness.

H2: The Influence of Candidate Experience on Selection Effectiveness

The analysis results show that candidate experience has a strong influence on selection effectiveness (β = 0.55; t = 6.20; p < 0.01). Candidates who undergo a positive recruitment experience are more likely to provide accurate and comprehensive information, thereby making it easier for HR to evaluate and select the right talent.

This finding is supported by Brown and Hesketh (2020), who noted that a positive recruitment experience strengthens a company's image, increases the likelihood of job offer acceptance, and encourages long-term commitment. In the context of this study, 85% of respondents held undergraduate degrees and were accustomed to using digital platforms, which suggests a relatively high level of trust in technology-based recruitment processes. As a result, the risks of job offer rejection and early turnover can be significantly minimized.

H3: The Influence of Technology Usage on Selection Effectiveness

Although the direct influence of technology usage on selection effectiveness is lower than that of candidate experience

($\beta = 0.38$; $t = 4.30$; $p < 0.01$), it remains statistically significant. Technology plays a critical role in expediting administrative processes, such as automated screening and applicant data analysis, thereby enhancing efficiency in the selection stage.

This finding is in line with Anderson (2019), who stated that implementing digital systems in the selection process can improve both efficiency and accuracy in identifying the right candidates. In other words, technology not only speeds up the process but also improves the quality of selection decisions made by organizations.

Overall, the findings of this study indicate that integrating technology into the recruitment process has a direct positive effect on selection effectiveness, while also indirectly enhancing selection quality through improved candidate experiences. A faster, more transparent, and interactive recruitment process fosters a positive candidate experience, enabling organizations to better identify and select the most suitable young talent. These findings underscore the importance of synergy between technological utilization and a human-centered approach in modern recruitment, as suggested by Weber & Tarba (2022), especially in Mataram City, which is predominantly inhabited by digital natives.

CONCLUSION

This study demonstrates that the implementation of digital technology in the recruitment process significantly enhances the effectiveness of selecting the young workforce in Mataram City. The results of the PLS-SEM analysis indicate that:

1. The use of technology has a positive effect on candidate experience ($\beta = 0.42$; $p < 0.01$).
2. Candidate experience significantly influences the effectiveness of selection ($\beta = 0.55$; $p < 0.01$).
3. Technology also has a direct positive impact on the effectiveness of selection ($\beta = 0.38$; $p < 0.01$).

Thus, the integration of technology use and the creation of a positive candidate experience is shown to be a key factor in improving the effectiveness of the recruitment and selection of the young workforce in Mataram City.

RECOMMENDATIONS

Based on the findings of this study, the following recommendations are proposed:

1. **For companies:** It is recommended that they continue to develop interactive and user-friendly digital recruitment systems in order to improve the candidate experience and expedite the selection process.
2. **For educational institutions and local governments:** It is important to provide training and enhance digital literacy among the younger generation so that they are optimally prepared to engage in technology-based recruitment processes.
3. **For future researchers**: It is recommended that they conduct qualitative explorations to delve deeper into candidates' perceptions of recruitment technology, as well as to broaden the geographic scope by comparing other local contexts in Indonesia.

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