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The Impact of Artificial Intelligence Implementation on Job Stability Through Job Polarization and Access to Training in Indonesia

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Abstract

The increasing adoption of artificial intelligence (AI) has significantly transformed organizational processes and labor market structures, raising concerns about employment outcomes, particularly job stability. This study investigates the impact of AI implementation on job stability in Indonesia, with job polarization and access to training examined as mediating variables. Using a quantitative research design, data were collected from 130 employees across various industries in Indonesia through a structured questionnaire measured on a five-point Likert scale. The data were analyzed using Structural Equation Modeling–Partial Least Squares (SEM-PLS 3). The results reveal that AI implementation has a significant direct effect on job stability. Moreover, AI implementation significantly increases job polarization, which negatively affects job stability, while simultaneously enhancing access to training, which positively influences job stability. The mediation analysis demonstrates that job polarization and access to training partially mediate the relationship between AI implementation and job stability, with access to training exhibiting a stronger mediating effect. These findings suggest that the employment consequences of AI are not purely deterministic but are shaped by organizational strategies and human capital investments. The study contributes to the literature on AI and the future of work by providing empirical evidence from an emerging economy context and highlights the critical role of inclusive training and reskilling initiatives in sustaining job stability amid AI-driven transformation.

Keywords: *Access to Training; Artificial Intelligence Implementation; Job Polarization; Job Stability; SEM-PLS*

1. Introduction

The rapid advancement of artificial intelligence (AI) has emerged as one of the most transformative forces shaping the future of work in the twenty-first century, as technologies such as machine learning, automation, data analytics, and intelligent decision-support systems become increasingly embedded in organizational processes across industries [1], [2]. Although AI implementation offers substantial benefits—including productivity gains, cost efficiency, and accelerated innovation—it also raises fundamental concerns regarding employment structures and job stability, particularly in developing and emerging economies like Indonesia, where a large workforce, heterogeneous skill levels, and uneven technological readiness characterize labor markets [3], [4]. Globally, the discourse on AI and employment has evolved from a simplistic notion of "job destruction" toward a more nuanced understanding of job transformation, in which AI reshapes task composition, alters skill requirements, and reconfigures occupational structures rather than merely eliminating jobs. One of the most prominent outcomes of this transformation is job polarization, whereby employment growth increasingly concentrates in high-skill, high-wage and low-skill, low-wage occupations, while middle-skill jobs stagnate or decline, thereby intensifying job instability among workers in routine and middle-skill roles who are more susceptible to displacement by automation and intelligent systems [1], [3]

In the Indonesian context, the implications of AI-driven job polarization are particularly critical, given that the labor market is dominated by a large share of routine and semi-skilled occupations, especially in manufacturing, services, and administrative sectors. As organizations increasingly adopt AI technologies to remain competitive in the digital economy, concerns arise over whether workers can sustain stable employment or instead face heightened job insecurity [5], [6]. Job stability—defined as the perceived continuity, security, and predictability of employment—is a vital determinant of individual well-being, organizational commitment, and broader socio-economic stability, as its decline may trigger increased stress, reduced productivity, and widening income inequality. Nevertheless, the effects of AI implementation on job stability are not uniform and largely depend on organizational and institutional responses, with access to training emerging as a key mitigating factor [6], [7].

Training and reskilling initiatives enable employees to adapt to technological change, develop new competencies, and transition into emerging roles generated by AI adoption. Accordingly, access to training functions as a strategic mechanism that can buffer the adverse employment effects of AI while reinforcing its positive outcomes; where training opportunities are limited or unevenly distributed, AI adoption may intensify job polarization and weaken job stability, whereas sustained organizational investment in employee development allows AI implementation to coexist with, or even enhance, job stability.

Despite the growing global literature on artificial intelligence (AI), employment, and workforce transformation, empirical evidence from emerging economies remains limited, as most existing studies are concentrated in developed countries with labor market institutions, education systems, and technological infrastructures that differ substantially from those in Indonesia. In addition, prior research often examines the impact of AI on employment outcomes in isolation, without sufficiently accounting for the mediating roles of job polarization and access to training, resulting in a critical research gap in understanding how AI implementation translates into job stability through these interconnected mechanisms.

Addressing this gap, the present study aims to empirically examine the impact of AI implementation on job stability in Indonesia by conceptualizing job polarization and access to training as mediating variables. Employing a quantitative approach, the study analyzes survey data from 130 respondents across various sectors using Structural Equation Modeling–Partial Least Squares (SEM-PLS 3). By integrating technological, labor market, and human capital perspectives, this research contributes by providing empirical evidence from an emerging economy context, advancing theoretical understanding through the simultaneous examination of key mediating mechanisms, and offering practical insights for organizational leaders and policymakers on the importance of inclusive training strategies in mitigating the risks of AI-driven workforce transformation, thereby emphasizing that the effect of AI on job stability is shaped not by technological determinism but by strategic human resource and policy interventions.

2. Literature Review

2.1 Artificial Intelligence Implementation in Organizations

Artificial intelligence (AI) refers to the capability of machines and computer systems to perform tasks that typically require human intelligence—such as learning, reasoning, problem-solving, and decision-making—and, within organizational contexts, its implementation involves integrating technologies including machine learning algorithms, robotic process automation, natural language processing, and predictive analytics into business processes and managerial decision systems to enhance efficiency, reduce costs, improve accuracy, and support strategic decision-making in competitive environments [8], [9]. From a technological change perspective, AI constitutes a form of skill-biased and task-biased technological change, as it not only replaces manual labor but also has the capacity to substitute for and complement cognitive tasks, including routine analytical and administrative work, thereby reshaping job roles, task composition, and required competencies rather than solely influencing productivity outcomes [10], [11]. Prior research indicates that AI's employment effects depend on whether organizations deploy these technologies as substitutes for human labor or as tools that augment employee capabilities, and in emerging economies such as Indonesia, this impact is further complicated by uneven adoption across sectors and organizations due to variations in technological readiness, investment capacity, and human capital, with larger firms and technology-intensive industries more likely to adopt AI than small and medium-sized enterprises, raising important questions about how AI implementation affects job stability across different occupational groups [10], [11].

2.2 Job Stability

Job stability refers to an individual's perception of continuity, security, and predictability in employment over time, encompassing both objective elements—such as the likelihood of retaining one's job—and subjective elements, including feelings of job security and confidence in future employment prospects, and it represents a critical dimension of decent work that shapes employee well-being, motivation, organizational commitment, and long-term career development [1], [2]. The literature emphasizes that technological change is a significant source of employment uncertainty, as shifts in task requirements or skill obsolescence can heighten job insecurity even when workers remain employed, with empirical evidence showing that automation and digitalization tend to reduce job stability for routine and middle-skill occupations while potentially enhancing stability for highly skilled workers whose tasks are complemented by technology [3], [4]. In the context of artificial intelligence, job stability is therefore shaped not only by the technology itself but also by organizational strategies and labor market institutions, as firms that implement AI without corresponding investments in workforce development may

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exacerbate job insecurity, whereas those prioritizing reskilling and internal mobility can sustain or even improve job stability, underscoring that the relationship between AI implementation and job stability is complex and mediated by structural and human capital factors.

2.3 Job Polarization

Job polarization refers to a labor market phenomenon in which employment growth concentrates at the high-skill and low-skill ends of the occupational distribution while middle-skill jobs experience decline, a pattern widely documented in both developed and developing economies and commonly linked to technological change, globalization, and organizational restructuring [12], [13]. From a theoretical perspective, job polarization is driven by the task-based nature of technological change, as routine tasks—whether manual or cognitive—are more easily automated, whereas non-routine analytical and interpersonal tasks are less susceptible to substitution; artificial intelligence intensifies this dynamic by extending automation into cognitive domains and increasing pressure on middle-skill occupations such as clerical, administrative, and certain technical roles. This polarization has direct implications for job stability, as workers in shrinking middle-skill occupations face higher risks of displacement and employment instability, high-skill workers may benefit from rising demand and greater job security, and low-skill jobs—despite being less automated—often offer limited stability due to informal arrangements and low wages [12], [14], making AI-driven job polarization a significant challenge for inclusive labor market outcomes in Indonesia, where employment remains heavily concentrated in routine and semi-skilled occupations.

2.4 Access to Training

Access to training refers to the availability and opportunity for employees to participate in learning, reskilling, and upskilling programs that enhance their knowledge and competencies, serving as a core component of human capital development that enables workers to adapt to technological and organizational change. Grounded in human capital theory, investments in education and training are expected to increase productivity and employability, thereby strengthening job stability and long-term career prospects [15], [16]; in the context of artificial intelligence implementation, this becomes particularly critical as employees must develop new digital, analytical, and adaptive skills to work effectively alongside intelligent systems. Empirical evidence consistently indicates that workers who receive continuous training are better positioned to transition into emerging roles, experience lower job insecurity, and maintain stable employment despite technological disruption [17], [18]. However, access to training is often uneven, with high-skilled employees and those in larger organizations more likely to benefit, while low- and middle-skilled workers face greater exclusion; in emerging economies, institutional constraints and limited resources can further restrict training access, potentially intensifying the adverse employment effects of AI and reinforcing job polarization.

3. Research Methods

3.1 Research Design

This study employs a quantitative research design to examine the impact of artificial intelligence (AI) implementation on job stability, with job polarization and access to training conceptualized as mediating variables, as the primary objective is to test hypothesized relationships among latent constructs and assess the strength and significance of these relationships using statistical techniques. The research adopts a cross-sectional approach, with data collected at a single point in time from respondents who have experienced AI implementation within their organizations. The proposed research model follows a causal–explanatory framework in which AI implementation functions as the exogenous variable, job stability as the endogenous variable, and job polarization and access to training as intervening variables, and Structural Equation Modeling–Partial Least Squares (SEM-PLS) is utilized to simultaneously evaluate the measurement model and the structural relationships among the constructs.

3.2 Population and Sample

The population of this study consists of employees working in organizations in Indonesia that have begun implementing AI-based technologies in their operational or managerial processes. Given the diversity of industries adopting AI, respondents were drawn from various sectors, including services, manufacturing, finance, education, and technology-related fields. A total of 130 respondents participated in the study. This sample size is considered adequate for SEM-PLS analysis, which is suitable for relatively small to medium samples and does not require strict assumptions of multivariate normality. The sampling technique used was non-probability sampling, specifically purposive sampling, as respondents were selected based on the criterion that they were aware of or

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directly experienced AI implementation in their workplace. This approach ensures that the collected data are relevant to the research objectives.

3.3 Data Collection Procedure

Data were collected through a structured questionnaire distributed electronically to respondents, allowing efficient coverage across diverse regions and organizational contexts in Indonesia. Prior to full deployment, the questionnaire was reviewed to ensure clarity, relevance, and alignment with the study variables, and participation was voluntary with assurances that responses would be kept confidential and used solely for academic purposes. The instrument comprised two main sections: the first gathered demographic information, including gender, age, education level, industry, and length of work experience, while the second measured the core research variables of artificial intelligence implementation, job polarization, access to training, and job stability.

3.4 Measurement of Variables

All constructs in this study were measured using multi-item indicators adapted from relevant prior literature and adjusted to the Indonesian organizational context, with responses captured on a five-point Likert scale ranging from 1 (“strongly disagree”) to 5 (“strongly agree”) to reflect respondents’ perceptions. Artificial intelligence implementation represents the extent to which AI technologies are integrated into organizational processes, decision-making, and task execution, with indicators capturing automation, AI-assisted decision support, and the use of intelligent systems in daily work activities. Job polarization measures employees’ perceptions of changes in occupational structures and task distribution resulting from AI adoption, particularly the decline of middle-skill tasks and the increased emphasis on high-skill or low-skill roles. Access to training refers to the availability and accessibility of organizational training, reskilling, and upskilling programs that support employees in adapting to AI-driven changes, including opportunities for skill development, the relevance of training content, and organizational support for learning. Job stability captures perceptions of employment security, continuity, and confidence in future job prospects, with indicators assessing the likelihood of job retention, perceived job security, and the stability of career paths within the organization.

3.5 Data Analysis Technique

Data analysis was conducted using Structural Equation Modeling–Partial Least Squares (SEM-PLS) with the assistance of SmartPLS version 3, as this technique is well suited for exploratory and predictive research, capable of handling complex models with mediating variables, and robust to relatively small sample sizes and non-normal data distributions. The analysis followed a two-stage procedure, beginning with the evaluation of the measurement model to assess construct reliability and validity through indicator reliability (outer loadings), internal consistency reliability (Cronbach’s alpha and composite reliability), convergent validity (average variance extracted), and discriminant validity. Subsequently, the structural model was examined to test the hypothesized relationships among variables by evaluating path coefficients, coefficients of determination (R^2), effect sizes, and the significance of both direct and indirect (mediating) effects using a bootstrapping procedure, with particular emphasis on assessing whether job polarization and access to training significantly mediate the relationship between AI implementation and job stability.

4. Results and Discussion

4.1 Respondent Profile

A total of 130 valid questionnaires were analyzed. Respondents represented multiple sectors and demographic backgrounds, ensuring sufficient variability in perceptions related to AI implementation.

Table 1. Respondent Demographics

Category	Description	Frequency	Percentage (%)
Gender	Male	72	55.4
	Female	58	44.6
Age	≤ 25 years	28	21.5
	26–35 years	54	41.5
	36–45 years	32	24.6
	> 45 years	16	12.4
Education	Diploma	24	18.5
	Bachelor	71	54.6
	Master/Doctoral	35	26.9
Industry	Services	46	35.4

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	Manufacturing	32	24.6
	Finance	22	16.9
	Education & Others	30	23.1

Table 1 presents the demographic profile of the 130 respondents, providing important contextual insight into the characteristics of the workforce represented in this study. In terms of gender, the sample is relatively balanced, with male respondents accounting for 55.4% and female respondents 44.6%, suggesting that perceptions of AI implementation and job stability are drawn from both male- and female-dominated work experiences. The age distribution indicates that the majority of respondents are in their prime working years, with 41.5% aged 26–35 years and 24.6% aged 36–45 years, while younger workers (≤25 years) constitute 21.5% and older workers (>45 years) 12.4%. This composition is particularly relevant, as workers in the 26–45 age range are typically more exposed to organizational digital transformation and are actively navigating skill adaptation in response to AI adoption. From an educational perspective, most respondents hold at least a bachelor's degree (54.6%), followed by those with postgraduate qualifications (26.9%), indicating a relatively well-educated sample that is likely to have direct interaction with AI-supported systems and decision-making processes; however, the presence of diploma holders (18.5%) also allows for capturing perspectives from semi-skilled roles that may be more vulnerable to job polarization. In terms of industry representation, the dominance of the service sector (35.4%) aligns with the rapid diffusion of AI in service-based activities such as administration, analytics, and customer interaction, while manufacturing (24.6%) and finance (16.9%) reflect sectors where automation and intelligent systems are increasingly reshaping job tasks and skill requirements. The inclusion of respondents from education and other sectors (23.1%) further enhances the diversity of organizational contexts examined.

4.2 Measurement Model Evaluation

The measurement model was evaluated using standard reliability and validity criteria, as summarized in Table 2, and the results indicate strong measurement quality across all constructs. Cronbach's alpha values ranged from 0.861 to 0.892, while composite reliability values ranged from 0.903 to 0.921, exceeding the recommended threshold of 0.70 and confirming adequate internal consistency. Convergent validity was also established, as the average variance extracted (AVE) values for AI implementation (0.684), job polarization (0.651), access to training (0.675), and job stability (0.700) all surpassed the minimum criterion of 0.50, indicating that the indicators adequately capture their respective constructs. In addition, discriminant validity was assessed using the Fornell–Larcker criterion, further supporting the distinctiveness of each construct within the model.

Table 2. Fornell–Larcker Criterion

Construct	AI	JP	AT	JS
AI	0.827			
JP	0.514	0.807		
AT	0.602	0.486	0.821	
JS	0.573	0.559	0.648	0.837

Table 2 presents the results of the Fornell–Larcker criterion, which was used to assess discriminant validity among the study constructs. The square roots of the average variance extracted (AVE), shown on the diagonal, are higher than the corresponding inter-construct correlations in each row and column, indicating that each construct shares more variance with its own indicators than with other constructs in the model. Specifically, AI implementation (0.827), job polarization (0.807), access to training (0.821), and job stability (0.837) all demonstrate adequate discriminant validity. The correlations among constructs are moderate, suggesting meaningful but not excessive relationships; for example, AI implementation is moderately correlated with job polarization (0.514) and access to training (0.602), reflecting the role of AI in reshaping job structures and influencing organizational investment in training. Similarly, job stability shows moderate associations with AI implementation (0.573), job polarization (0.559), and access to training (0.648), supporting the theoretical expectation that job stability is jointly influenced by technological change, labor market dynamics, and human capital factors.

4.3 Structural Model Results

The structural model was assessed using path coefficients, t-values, p-values, and coefficients of determination (R^2), with the results indicating satisfactory explanatory power. The R^2 values show that AI implementation explains 26.4% of the variance in job polarization and 36.2% of the variance in access to training, while the combined effects of AI implementation, job polarization, and access to training explain 52.1% of the variance in job stability. This indicates a moderate-to-strong level of explanatory power for the model, suggesting that the proposed variables meaningfully capture key mechanisms through which AI implementation influences job stability, thereby providing a solid basis for subsequent hypothesis testing.

Table 3. Direct Effects

Path	β	t-value	p-value	Result
AI → Job Stability	0.218	2.415	0.016	Supported
AI → Job Polarization	0.514	6.983	0.000	Supported
AI → Access to Training	0.602	8.345	0.000	Supported
Job Polarization → Job Stability	−0.291	3.767	0.000	Supported
Access to Training → Job Stability	0.452	5.892	0.000	Supported

Table 3 reports the results of the direct effects in the structural model and demonstrates strong empirical support for all hypothesized relationships. The direct effect of AI implementation on job stability is positive and significant ($\beta = 0.218$, $t = 2.415$, $p = 0.016$), indicating that, on average, greater integration of AI within organizations is associated with higher perceived job stability, potentially reflecting the role of AI as a complementary technology when supported by appropriate organizational practices. At the same time, AI implementation has a strong and significant positive effect on job polarization ($\beta = 0.514$, $t = 6.983$, $p < 0.001$), confirming that AI adoption intensifies shifts in occupational structures and task distribution, particularly affecting middle-skill roles. AI implementation also exhibits a robust positive effect on access to training ($\beta = 0.602$, $t = 8.345$, $p < 0.001$), suggesting that organizations adopting AI are more likely to invest in training and reskilling initiatives to support workforce adaptation.

Furthermore, job polarization has a significant negative effect on job stability ($\beta = -0.291$, $t = 3.767$, $p < 0.001$), indicating that increased polarization is associated with reduced employment security, especially for workers in vulnerable occupational groups. In contrast, access to training shows a strong positive effect on job stability ($\beta = 0.452$, $t = 5.892$, $p < 0.001$), highlighting the critical role of training in enhancing employees' perceptions of job security and continuity.

4.5 Mediation Analysis

Bootstrapping was used to test indirect effects.

Table 4. Indirect (Mediating) Effects

Indirect Path	β	t-value	p-value	Mediation Type
AI → JP → JS	−0.150	3.426	0.001	Partial Mediation
AI → AT → JS	0.272	4.982	0.000	Partial Mediation

Table 4 presents the results of the indirect effect analysis, providing evidence of the mediating roles of job polarization and access to training in the relationship between AI implementation and job stability. The indirect path from AI implementation to job stability through job polarization is negative and statistically significant ($\beta = -0.150$, $t = 3.426$, $p = 0.001$), indicating that AI adoption indirectly reduces job stability by intensifying job polarization, which in turn undermines employment security. This finding supports the argument that the automation of routine and middle-skill tasks represents a destabilizing channel through which AI affects workers' perceptions of job continuity. Conversely, the indirect effect of AI implementation on job stability through access to training is positive and significant ($\beta = 0.272$, $t = 4.982$, $p < 0.001$), demonstrating that AI adoption can enhance job stability when it is accompanied by increased opportunities for training and reskilling. The presence of significant direct effects alongside these indirect effects indicates partial mediation in both cases, suggesting that AI implementation influences job stability through multiple simultaneous pathways.

4.6 Discussion

The findings provide strong empirical evidence that artificial intelligence (AI) implementation significantly shapes job stability in Indonesia through both direct and indirect mechanisms. The positive direct effect of AI on job stability indicates that AI adoption can enhance employees' perceptions of employment security when it is experienced as a supportive, efficiency-enhancing technology rather than a direct substitute for human labor. This result aligns with the augmentation perspective of AI, which emphasizes the complementary role of intelligent systems in improving work processes, supporting decision-making, and strengthening organizational performance without necessarily displacing workers [19], [20].

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At the same time, the strong positive relationship between AI implementation and job polarization confirms concerns raised by task-based and routine-biased technological change theories. AI adoption disproportionately affects middle-skill occupations by automating routine cognitive and administrative tasks, thereby restructuring occupational demand and increasing employment vulnerability for certain groups of workers. The significant negative effect of job polarization on job stability empirically validates this structural risk within the Indonesian labor market, where a large share of employment remains concentrated in routine and semi-skilled roles.

Crucially, access to training emerges as a key protective and balancing mechanism in this relationship. The strong association between AI implementation and access to training suggests that organizations adopting AI are more likely to invest in workforce development, while the substantial positive effect of training on job stability highlights its strategic importance in enabling skill adaptation, reskilling, and career continuity. The mediation analysis further demonstrates that although job polarization transmits negative effects of AI on job stability, access to training more effectively offsets these risks, reinforcing the view that the employment impact of AI is not technologically deterministic but shaped by human capital strategies. Overall, these findings extend the AI–employment literature by showing that in an emerging economy such as Indonesia, job stability can be sustained when AI adoption is accompanied by inclusive and accessible training systems, underscoring the need for policymakers and organizational leaders to align AI strategies with workforce development policies to achieve sustainable and equitable labor market outcomes.

5. Conclusion

This study provides empirical evidence on how artificial intelligence implementation influences job stability in Indonesia through the interrelated mechanisms of job polarization and access to training, demonstrating that AI adoption significantly affects job stability both directly and indirectly by reshaping employment conditions rather than merely replacing labor. The findings show that AI-driven job polarization constitutes a structural challenge that increases employment vulnerability among workers in routine and middle-skill occupations, thereby weakening perceived job stability, while access to training plays a crucial compensatory role by enabling employees to adapt to changing job requirements, sustain employability, and maintain higher levels of job stability. The stronger mediating effect of access to training compared to job polarization underscores the central importance of human capital development in managing AI-driven workforce transformation. From a practical standpoint, the results highlight the need for organizations to align AI adoption with comprehensive training and development strategies, emphasizing continuous learning, digital skills, and adaptive competencies to ensure that technological advancement supports sustainable employment rather than exacerbating labor market inequalities. At the policy level, the findings stress the importance of inclusive workforce policies, robust vocational and lifelong learning systems, and stronger collaboration between industry and educational institutions.

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