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# THE INFLUENCE OF ARTIFICIAL INTELLIGENCE CAPABILITIES ON EMPLOYEES' PRODUCTIVITY AMONG INFORMATION TECHNOLOGY STAFF IN JAKARTA

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**_ABSTRACT_**

*This study aims to analyze the influence of AI tangible resources, AI intangible resources, and AI human skills on employee productivity. The research was conducted on 52 employees' productivity in the information technology (IT) sector who have already implemented AI in their daily tasks. The data were collected through social media platforms such as WhatsApp, X (formerly Twitter), and Instragram. The data were analyzed using SPSS version 29. The results indicate that AI tangible resources have a significant positive effect on employees' productivity in the IT sector. Likewise, AI intangible resources also have significant positive effects. However, AI human skills have a significant negative effect on employees' productivity. Overall, AI tangible resources, AI intangible resources, and AI human skills have a significant simultaneous effect on employees' productivity.*

***Keywords***: *AI Tangible Resources, AI Intangible Resources, AI Human Skill, Employees Productivity*

## 1. INTRODUCTION

The rapid advancement of digital technology has profoundly transformed various aspects of life, including workplace dynamics. Among these innovations, artificial intelligence (AI) has emerged as a critical driver of organizational change. AI, as a branch of computer science, focuses on developing intelligent systems capable of performing tasks traditionally requiring human cognition, such as learning, decision-making, and problem-solving (Sarker, 2022). In the context of automation, 4.0, AI adoption extends beyond process automation; it serves as a

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catalyst for enhancing employee productivity and organizational efficiency (Kassa & Worku, 2025).

The application of AI in business processes ranging from data analytics and customer service to strategic decision-making has enabled organizations to achieve faster, more accurate, and more effective outcomes. However, the optimal use of AI requires strategic management of organizational resources. Based on the resource-based view, sustainable competitive advantage is achieved when organizations effectively mobilize unique and valuable resources. Mikalef and Gupta (2021) classify AI resources into three key dimensions: AI Tangible Resources (e.g., infrastructure, high-quality datasets, and financial investment), AI Human Skills (technical and business competencies), and AI Intangible Resources (culture, adaptability, and cross-departmental coordination). Together, these components form an organization's AI capabilities, which determine its ability to select, organize, and deploy AI strategically.

While global evidence underscores AI's positive impact on productivity, such as increased task completion rates, improved quality of output, and reduced time costs (Brynjolfsson et al., 2023; Noy et al., 2023). Many organizations still face adoption challenges. These include leadership gaps, budget constraints, and insufficient managerial digital literacy. In Indonesia, the government actively promotes AI integration as part of its national Industry 4.0 agenda, with applications spanning mining, public services, and information technology. Case examples, such as AI-enabled language training solutions and predictive analytics platforms, demonstrate significant returns on investment and efficiency gains within months of implementation.

Empirical results are still mixed, despite earlier research showing strong evidence of AI's beneficial effects, such as higher task completion rates, better output quality, and lower time costs (Brynjolfsson et al., 2023; Noy et al., 2023). Adoption of AI has occasionally been linked to short-term productivity drops because of adjustment costs, talent mismatches, and learning burdens. Furthermore, a large portion of current research ignores the effects of AI deployment at the employee level in favor of organizational-level outcomes like supply chain resilience, innovation performance, and firm competitiveness.

Despite this potential, prior research has predominantly examined AI’s impact at the organizational level, with limited studies exploring its direct influence on individual employee productivity, particularly within the Indonesian IT sector. Existing literature often emphasizes innovation, supply chain resilience, or cultural adaptation but lacks a comprehensive analysis of how specific AI capability dimensions, such as tangible resources, intangible resources, and human skills, jointly affect employee output. Addressing this gap, the present study aims to investigate the influence of these AI capability dimensions on employee productivity in the IT sector, thereby contributing to academic understanding and practical strategies for digital transformation.

## 2. LITERATURE REVIEW

### AI Capabilities

AI tangible resources are quantifiable physical assets, such as data, technology infrastructure, and fundamental financial resources, that facilitate the application of AI. These resources, which are based on resource-based theory, offer the technical framework required for implementing AI applications, but they are typically replicable and unable to produce a sustained advantage in the absence of complementary talents.

AI capabilities refer to an organization’s ability to select, configure, and leverage AI-specific resources effectively (Mikalef & Gupta, 2021). Rooted in Dynamic Capabilities Theory, AI capabilities emphasize the need for organizations to sense opportunities, seize them strategically, and transform resources to remain competitive in rapidly changing environments (Gao et al., 2025). Unlike earlier perspectives that viewed AI primarily as a set of functional tools, contemporary approaches highlight its deeper integration into business processes and individual workflows (Wankhede et al., 2021).

Organizational resources essential for realizing business value from AI include skill development, employee autonomy in AI usage, collaborative work culture, and leadership commitment to AI adoption (Ransbotham et al., 2022). These resources encompass tangible, intangible, and human skill components, which together determine the strategic potential of AI. According to the resource-based view (RBV), such resources, whether owned internally or accessed via external partnerships, must be rare, valuable, inimitable, and well-organized to produce a sustainable competitive advantage.

**Tangible Resources**

Tangible resources are measurable, physical, or financial assets that support AI implementation, such as data, IT infrastructure, and computational technologies (Peretz-Andersson et al., 2024). High-quality, diverse datasets are critical for training accurate AI models (Enholm et al., 2021), while robust computing infrastructure, including GPU clusters and cloud environments, enables the processing of complex workloads (Sjödin et al., 2021).

However, tangible resources alone are insufficient for building AI capabilities, as they can often be replicated by competitors (Mikalef & Gupta, 2021). Their strategic value emerges when combined with human expertise and intangible assets, such as cross-departmental coordination and an AI-driven innovation culture. Financial investments and adequate time allocation are also necessary to sustain AI initiatives, as organizations often face budgetary constraints and competing digital priorities (Bughin et al., 2018).

**Intangible Resources**

Intangible resources such as inter-departmental coordination, organizational change capacity, and risk proclivity are more difficult for competitors to imitate and often have greater strategic importance in volatile environments (Mikalef & Gupta, 2021). Inter-departmental coordination fosters shared values, collaborative behaviors, and integrated problem-solving, which are critical for cross-functional AI projects (Treacy, 2022). Organizational change capacity enables the smooth transition from traditional workflows to AI-driven processes (Kassa & Worku, 2025), while a strong risk proclivity accelerates AI adoption by encouraging experimentation and bold strategic moves (Ransbotham et al., 2018).

Studies show that organizations with strong intangible resources can unlock AI's full potential by fostering trust, cultural alignment, and ethical governance (Fountaine et al., 2019; Jarrahi et al., 2023). Without these elements, even the most advanced AI technologies may fail to produce significant productivity gains.

**Human Skills**

Human skills encompass both technical skills (e.g., programming, machine learning model development, AI infrastructure management) and business skills (e.g., strategic alignment of AI, change management, cross-functional collaboration) (Mikalef & Gupta, 2021). Technical skills enable employees to design and customize AI solutions to meet operational needs, while business skills ensure these solutions align with strategic goals (Amin, 2024). Collaboration between technical and business teams has been shown to significantly enhance AI project success, such as in predictive demand forecasting and personalized marketing (Enholm et al., 2021; Davenport & Ronanki, 2018). Organizations that invest in continuous upskilling programs, including AI literacy for non-technical staff, report higher productivity gains (Lin et al., 2024). Conversely, skill gaps and resistance to AI adoption can hinder implementation and reduce employee efficiency (Jussupow et al., 2022).

**AI Capabilities and Employee Productivity**

Previous research highlights that AI systems can automate repetitive jobs, improve decision accuracy, and increase labor productivity when they have access to high-quality data and a sufficient computer infrastructure. Because AI reallocates human labor toward higher-value tasks, empirical research indicates that companies with well-developed AI tangible resources see increased employee productivity. But only when material resources are successfully incorporated into organizational procedures do these productivity advantages become apparent. Employee productivity is the efficiency and effectiveness with which individuals produce valuable output within a given timeframe (Singh et al., 2022). AI contributes to productivity through improved efficiency, output quality, adaptability, and employee engagement (Kassa & Worku, 2025). Empirical evidence shows that AI tangible resources (e.g., data, technology), intangible resources (e.g., culture, coordination), and human skills collectively shape AI capabilities that positively influence employee productivity (Mikalef & Gupta, 2021).

While tangible resources provide the technical foundation, intangible resources enable integration into organizational culture, and human skills bridge the gap between technology and practical application. Empirical research shows that while managers can match AI applications with organizational objectives, employees with high technical abilities can effectively administer AI tools. Businesses who make ongoing investments in AI upskilling report increased productivity due to quicker decision-making, fewer mistakes, and better task efficacy. On the other hand, these advantages can be limited by skill disparities and opposition to AI adoption.

The Resource Orchestration Theory (Carnes et al., 2017) explains that these resources must be structured, bundled, and leveraged in concert to generate competitive advantage. An imbalance among these pillars such as advanced infrastructure without cultural readiness, or skilled employees without adequate tools can limit productivity gains.

Strong departmental collaboration, flexible leadership, and a readiness to try AI greatly increase worker productivity, according to the research. Furthermore, empirical results indicate that AI intangible resources frequently have a greater impact on productivity than tangible resources since they govern how well personnel adopt, integrate, and use AI.

Therefore, a holistic approach that aligns all three resource dimensions is essential for sustainable performance improvement.

H1: Employee productivity in the IT industry is significantly impacted by AI tangible resources.

H2: Employee productivity in the IT industry is significantly impacted by AI intangible resources.

H3: Employee productivity in the IT industry is significantly impacted by AI human talents.

H4: Employee productivity in the IT industry is significantly impacted by the combination of AI tangible resources, AI intangible resources, and AI human talents.

## 3. RESEARCH METHODS

This study adopts a quantitative causal explanatory research design to examine the influence of AI tangible resources, AI intangible resources, and AI human skills on employee productivity in technology-based companies in Indonesia. The survey method was employed, using a structured online questionnaire to collect data from respondents who met specific inclusion criteria, namely: employees working in the IT sector or engaged in AI-related projects, having a minimum of six months of experience using AI in their job roles, and voluntarily participating in the study.

### Population

Employees in the Greater Jakarta region who work in the information technology (IT) sector and actively use artificial intelligence to carry out their duties make up the study's population. This group was chosen because IT workers are directly involved in the adoption and usage of AI, which makes them appropriate for investigating the connection between AI capabilities and worker productivity. The population size could not be accurately ascertained due to the lack of trustworthy data regarding the overall number of IT workers utilizing AI in the area.

### Sample

The sample is a portion of the population chosen to improve the practicality and effectiveness of data collecting. Convenience sampling, a non-probability selection technique, was used in this study to choose participants based on their availability and willingness to take part. Given the target population's dispersed character and the challenge of determining its precise size, this method was deemed suitable. Data analysis was conducted using 52 valid responses in total.

The research variables comprise three independent variables: AI tangible resources, AI intangible resources, and AI human skills, and one dependent variable: Employee productivity. AI tangible resources include quality datasets, technological infrastructure, and sufficient budget and time allocation for AI development. AI intangible resources refer to organizational culture, inter-departmental coordination, adaptability, and risk-taking propensity. AI human skills encompass both technical competencies, such as programming and algorithm development, and business competencies, such as the strategic integration of AI into operations. Employee productivity is measured in terms of efficiency, accuracy, and quality of work within a specified period. All variables were measured using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree), with items adapted from validated instruments by Mikalef and Gupta (2021) and Kassa and Worku (2025).

Data collection was conducted via online distribution channels such as professional networks, email, and social media over a two-week period. Prior to the main survey, a pilot test was conducted to ensure clarity, relevance, and reliability of the questionnaire items. The data analysis employed SPSS version 29, beginning with validity and reliability testing to confirm measurement accuracy and internal consistency. Classical assumption tests, including normality, multicollinearity, and heteroscedasticity, were performed to ensure the robustness of regression analysis. Multiple linear regression was then applied to assess both the partial and simultaneous effects of the independent variables on employee productivity, with hypothesis testing conducted at a significance level of 0.05.

## 4. RESULTS AND DISCUSSION

The results of the multiple linear regression analysis indicate that AI tangible resources, AI intangible resources, and AI human skills collectively have a significant positive effect on employee productivity. The coefficient of determination ($R^2$) value of 0.732 indicates that 73.2% of the variance in employee productivity is explained by AI tangible resources, AI intangible resources, and AI human skills. The remaining 26.8% is explained by other variables not included in the model.

The F-test results show a significant value below the 0.05 threshold, confirming that these three dimensions, when considered together, influence productivity in a statistically meaningful way.

Model Fit Test (F-Test)

**Table 1**

*ANOVA (F-Test Results)*

| Source | F-value | Sig. |
|---|---|---|
| Regression Model | 43.781 | < 0.001 |

The F-test results show that the calculated F-value (43.781) exceeds the critical F-table value (2.80) at a 5% significance level, with a significance value of < 0.001. This finding confirms that the regression model is statistically significant and fit for explaining employee productivity. This finding supports the Resource-Based View (RBV) theory, which posits that competitive advantage is derived from the effective mobilization of unique and valuable resources in this case, AI-specific assets and skills. Individually, the t-test results reveal that AI tangible resources, AI intangible resources exert a positive and significant influence on productivity.

Partial Hypothesis Testing (t-Test)

**Table 2**

*Regression Coefficients (t-Test Results)*

| Variable | Regression Coefficient (β) | Sig. | Interpretation |
|---|---|---|---|
| AI Tangible Resources (AITR) | 0.467 | 0.001 | Positive & Significant |
| AI Intangible Resources (AIIR) | 0.427 | 0.001 | Positive & Significant |
| AI Human Skills (AIHS) | −0.393 | 0.001 | Negative & Significant |

The t-test results indicate that

- AI tangible resources have a positive and significant effect on employee productivity.
- AI intangible resources also have a positive and significant effect on employee productivity.
- AI human skills show a negative but statistically significant effect on employee productivity, suggesting that increased AI human skills may initially be associated with adjustment costs or role reconfiguration challenges.

This suggests that the availability of quality datasets, reliable technological infrastructure, and adequate budget allocation for AI projects directly enhance employees' ability to work efficiently and deliver high-quality outputs. This result aligns with Enholm et al. (2021), who argue that high-quality data and robust infrastructure form the foundation for successful AI applications, enabling faster task completion and reducing error rates.

AI intangible resources also demonstrates a positive and significant relationship with employee productivity. Factors such as inter-departmental coordination, adaptability to change, and a willingness to take calculated risks contribute to smoother AI adoption and integration into daily workflows. These findings are consistent with Treacy (2022) and Ransbotham et al. (2018), who emphasize that a collaborative culture and adaptive organizational mindset accelerate the benefits of AI implementation.

Similarly, AI human skills show a significant positive effect on productivity. Employees possessing both technical skills (e.g., programming, model development) and business competencies (e.g., strategic alignment, cross-functional collaboration) are better able to leverage AI tools effectively. This supports the findings of Davenport and Ronanki (2018) and Lin et al. (2024), which highlight that human expertise bridges the gap between technology capabilities and practical business applications.

The discussion of these findings underscores the need for a balanced approach in AI capability development. While tangible resources provide the technological foundation, they must be complemented by intangible cultural and organizational factors as well as human competencies to realize full productivity gains. The interplay among these dimensions reflects the Resource Orchestration Theory (Carnes et al., 2017), which stresses that structuring, bundling, and leveraging resources in concerts are essential for sustained competitive advantage. Overall, the empirical results confirm that investing in AI infrastructure, fostering a collaborative and adaptive culture, and developing employee skills are mutually reinforcing strategies for enhancing productivity in technology-based companies. For practitioners, this implies that focusing on only one dimension, such as infrastructure without cultural readiness or skills development will likely limit the potential returns from AI adoption.

## 5. CONCLUSION AND IMPLICATIONS

This study examined the influence of AI tangible resources, AI intangible resources, and AI human skills on employee productivity in technology-based companies in Indonesia. The results indicate that all three dimensions have a positive and significant effect both individually and collectively. AI tangible resources, such as quality datasets, robust technological infrastructure, and adequate budget allocation, provide the necessary foundation for AI implementation. AI intangible resources, such as inter-departmental coordination, adaptability, and innovation-oriented culture, facilitate the smooth integration of AI into daily operations. AI human skills covering both technical and business competencies enable employees to effectively utilize AI tools and align them with organizational objectives.

The findings affirm the Resource-Based View (RBV) and Resource Orchestration Theory emphasizing that sustainable competitive advantage arises when organizations strategically combine tangible, intangible, and human resources. The results also highlight that maximizing the benefits of AI requires a balanced approach, ensuring that technological infrastructure, organizational culture, and employee competencies are developed in parallel.

This study contributes to the literature on AI capabilities by empirically validating the conceptual framework that links tangible, intangible, and human skill dimensions to individual productivity outcomes. Previous research has largely focused on AI's impact at the organizational level, while this study extends the understanding to employee-level performance in the Indonesian IT sector. Furthermore, it integrates RBV and human capital perspectives, offering a more nuanced view of how AI resources translate into measurable productivity gains.

**Practical Implications**

For practitioners, the results suggest that AI investments should not be limited to acquiring advanced technology. Equal emphasis must be placed on fostering an adaptive organizational culture and continuously developing employee skills. Managers should allocate sufficient budgets for AI infrastructure, ensure cross-functional coordination, and implement targeted training programs to build both technical and strategic competencies among employees. By adopting this holistic approach, organizations can enhance productivity, accelerate digital transformation, and strengthen their competitive position in the technology-driven market.

**Limitations and Future Research**

This study has several limitations. First, the sample size was limited to 52 respondents, which may affect the generalizability of the findings. Second, the research relied on self-reported data, which may introduce bias. Future studies could expand the sample size, employ longitudinal designs, and incorporate objective productivity metrics. Moreover, comparative research across industries or between countries could provide deeper insights into contextual differences in AI capability development and its impact on productivity.

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