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AI ADOPTION IN THE DIGITAL CREATIVE INDUSTRY: WHY TALENT READINESS OVERWEIGHS ORGANIZATIONAL SUPPORT?

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ABSTRACT

The rapid development of artificial intelligence (AI) is fundamentally reshaping the landscape of digital transformation in various sectors. This phenomenon is particularly critical in the digital creative industry and application development startups, which rely heavily on technological innovation while operating in dynamic and highly competitive business environments. However, despite the promised operational benefits, the AI adoption rate among workers still shows significant variation. This study aims to empirically analyze the key determinants of AI adoption among workers in Jakarta's digital creative sector by focusing on the role of talent capabilities, talent management strategies, IT infrastructure, and organizational support. This study uses a quantitative approach through a structured survey of 226 workers in digital startups located in Jakarta and is analyzed using binary logistic regression to test the predictive variables. The statistical results showed that talent capabilities had a positive and significant effect on AI adoption, proving that individual technical competence is the primary driver of usage behavior. Conversely, talent management strategies, IT infrastructure, and organizational support did not show a statistically significant influence. These findings indicate that AI adoption in the creative economy context is driven more by individual readiness than by top-down managerial or structural factors. Consequently, entrepreneurs in the creative industry should prioritize strengthening individual talent capabilities through targeted upskilling and continuous learning programs as the main foundation for driving effective digital transformation and ensuring business sustainability.

Keywords: *Artificial Intelligence, Talent Capabilities, Talent Management, Technology Adoption*

INTRODUCTION

Artificial intelligence (AI) currently plays a crucial role in driving digital transformation across various economic sectors, including technology-based companies and digital startups. AI is believed to be transforming current work structures and behaviors (Sunandar et al., 2025). This is because AI is no longer understood solely as automation or a new technology, but rather as a system capable of increasing efficiency and productivity and supporting data-driven decision-making (Balbaa & Abdurashidova, 2024). In the context of Indonesia's digital economy, AI adoption is becoming increasingly relevant as competitive pressures and efficiency demands increase in an increasingly dynamic business environment.

Indonesia's digital ecosystem is dominated by small and medium-sized enterprises (MSMEs), including those in the digital startup subsector, which contribute significantly to the national economy (Kadin, 2024). These MSMEs play a significant role in generating gross domestic product (GDP), absorbing labor, and promoting economic equality (Deby Laras Wati et al., 2024; Yulya Ammi Hapsari et al., 2024). In recent years, MSME involvement in the digital ecosystem has also shown rapid growth and become a key factor in the acceleration of increasingly widespread digitalization (Kadin, 2024). These developments illustrate that digital transformation, including the adoption of AI, is no longer merely a temporary, non-critical issue for large companies, but also impacts organizations operating on a more flexible and dynamic scale, such as digital startups.

In the face of Industry 4.0 and the post-pandemic era, business actors in the creative sector are pressured to transform. Ardana et al. (2023)) emphasize that creative innovation and digital branding are no longer optional but essential for survival and maintaining competitiveness. However, successful digital transformation requires more than just tools; it demands a shift in mindset and competence. As highlighted by Aminah et al. (2021), developing digital entrepreneurship understanding and soft skills is critical for MSMEs and creative actors to effectively utilize technologies like Artificial Intelligence.

However, AI adoption at the organizational and employee levels still faces various fundamental and substantive issues. Several previous studies have shown that the challenge of adopting new technologies is often not matched by talent readiness, particularly in terms of digital literacy and analytical skills (Dinul Khaq et al., 2024; Kumar, 2024). Furthermore, AI technology is often perceived as a complex system that does not always align with dynamic and rapidly changing business models, such as those often encountered in MSMEs and digital startups (Dahlqvist & Pivén, 2020; Lai et al., 2025). This situation makes the level of AI adoption at the employee level very complex, and there is no consensus on a single definition that describes the most ideal adoption process.

Discussed in the previous paragraph, the challenges are becoming increasingly serious and complex, especially in the context of digital startups in DKI Jakarta Province. Currently, digital startups operate within relatively lean organizational structures, with a high degree of reliance on individual worker capabilities and advanced technology (Ghezzi & Cavallo, 2020). Startup talent is often required to possess multi-skills and a high degree of adaptability to changes in technology, job types, and work experience within the digital startup environment. Therefore, talent capabilities, such as basic digital literacy, analytical skills, adaptability, and technological independence, are key factors in determining the success of AI adoption in the workplace.

In addition to individual factors, literature studies also discuss the importance of talent management in managing the technology adoption process (Desty Febrian et al., 2024; El-Haraki, 2023; Ferreira et al., 2024; Sharipov et al., 2020). In general, these studies explore information on training programs, upskilling, coaching, and talent retention strategies, which are seen as important instruments to ensure that workers are not only able to use technology but also integrate it into their daily work activities (Mardhiah Selamat et al., 2024). The success of AI adoption is also influenced by leadership readiness and organizational commitment to designing a long-term technology-based strategy (Natarajan et al., 2024; Tiwari et al., 2022).

Although research on AI adoption continues to grow, research specifically examining the role of talent capabilities and talent management in AI adoption among digital startup workers in Indonesia remains relatively limited. Most studies focus on the risks and opportunities of AI adoption in general, or on the role of AI in talent management functions, without empirically examining these factors at the employee level (Lourens et al., 2024; Pillai & Sivathanu, 2020). Therefore, this study aims to analyze the factors influencing artificial intelligence adoption among digital startup workers in Jakarta, with an emphasis on the role of talent capabilities, talent management strategies, information technology infrastructure and processes, and organizational support factors.

Based on this description, this study aims to analyze the factors influencing AI adoption among digital startup workers in DKI Jakarta. Specifically, this study examines the role of talent capabilities, talent management strategies, information technology infrastructure and processes, and organizational support factors in determining the probability of AI adoption at the employee level. Using a quantitative approach through logistic regression (Fleiss et al., 1986; Sadoughi et al., 2020; Stoltzfus, 2011), this study is expected to provide an empirical contribution to the technology adoption literature, while also serving as a practical reference for startups and policymakers in designing digital talent development strategies.

Theoretically, this research synthesizes the Technology-Organization-Environment (TOE) framework with the Resource-Based View (RBV). The TOE framework provides a comprehensive lens to categorize adoption drivers into technological contexts (IT infrastructure), organizational contexts (management support and strategy), and environmental contexts (competitive pressure) (Oliveira & Martins, 2010). Meanwhile, the RBV perspective posits that firm-specific resources—particularly human capital—are the primary drivers of competitive advantage because they are valuable, rare, and inimitable (Barney, 1991). By integrating these views, this study argues that while TOE factors provide the structural necessity for AI adoption, the actual implementation success is heavily determined by human talent readiness as emphasized in RBV (Xiong et al., 2021).

METHOD OF IMPLEMENTATION

In general, this study uses a quantitative approach with an explanatory research design(Toyon, 2021). This approach was used to analyze the factors influencing AI adoption among digital startup talent in Jakarta. The quantitative approach was chosen to empirically test the relationship between the independent and dependent variables based on survey data (Creswell, 2011; LIST, 2002).

The research subjects were talent, who are also permanent employees, at digital startups located in Jakarta. Digital startups were chosen due to their dynamic, technology-

driven organizational characteristics and high levels of innovation pressure (Ries, 2011; Skala, 2019). The unit of analysis in this study is the individual worker, as AI adoption is measured by the level of worker usage and involvement in daily work activities. This definition will be referred to as "talent" throughout this study for ease of reference.

The research data was obtained through a survey using a structured questionnaire. A total of 226 respondents were collected for this study, which were then analyzed as the research sample. Furthermore, respondents were selected based on the criteria of being active employees at digital startups operating in the Jakarta area. Data collection was conducted between May and July 2025.

The dependent variable in this study is the adoption of artificial intelligence, which is coded as a dichotomous variable (Xlog), with a value of 1 indicating the presence of AI adoption and a value of 0 indicating the absence of AI adoption. The independent variables consist of four main constructs as in Table 1 below.

Table 1. Operational Variable

No	Variable	Description	Sources
1	Talent Capability (KT),	measured through indicators of basic digital literacy, adaptability and willingness to learn, resilience under pressure, basic analytical skills, and technological independence	(Akter et al., 2019; Fahmi et al., 2020)
2	Talent Management (MT)	Strategy, which includes digital skills-based recruitment, artificial intelligence training and upskilling, internal coaching and mentoring, digital performance management, and digital talent retention	(Bambang Masudi et al., 2025; Collings & Mellahi, 2009; Natarajan et al., 2024)
3	Information Technology (IT)	which includes device and internet access, information system integration, software and AI-based tool support, and ongoing technology investment	(Bottini et al., 2017; Prud'homme, 2004; Winters, 2014)
4	Organizational Support Factors (FP),	which include management commitment to technology, external support, pro-technology organizational culture, internal policies that support innovation, and innovative leadership	(Hofstede, Geert, 2010; O'Reilly et al., 2022; Oyinlade & Christo, 2020).

All indicators were measured using a Likert scale and then processed into a composite index for each independent variable. Data analysis was performed using binary logistic regression, considering the dichotomous nature of the dependent variable. Logistic regression is used to estimate the probability of AI adoption based on variations in the independent variables (Fleiss et al., 1986; Okumura & Naito, 2006; Stoltzfus, 2011). The regression model used is formulated as follows:

$$\ln\left(\frac{P(Xlog=1)}{1-P(Xlog=1)}\right) = \beta_0 + \beta_1 KT + \beta_2 MT + \beta_3 ID + \beta_4 FP$$

Model feasibility was tested using the Likelihood Ratio Test, while the model fit was evaluated using the Pseudo R^2 (McFadden) value. Regression results were interpreted by considering the regression coefficient, significance level, and odds ratio to explain the strength of each independent variable's influence on the probability of AI adoption (Neuman, 2014).

RESULTS AND DISCUSSION

The adoption of new technologies in organizations is a process influenced by various interrelated factors, including individual, managerial, technical, and external environmental aspects (Sadoughi et al., 2020). Studies show that the success of technology adoption is not solely determined by the availability of infrastructure or information systems but also depends heavily on the talent involved in the process (Chang et al., 2025; Sirkemaa, 2019). In the context of digital technology and artificial intelligence adoption, these factors interact to shape an organization's ability to translate the potential of technology into tangible value for performance and decision-making (Akter et al., 2019).

The individual level, talent capabilities and basic digital literacy are the main foundations for driving the adoption of new technologies (Akbar & Hardiyati, 2021). Talent with technical understanding, analytical skills, and readiness to adapt to digital change play a crucial role in reducing resistance and accelerating technology implementation. Akter et al. (2019) showed that the impact of technology on organizational performance is significantly mediated by talent capabilities that lead analytical processes and strategic decision-making. Furthermore, dynamic capabilities such as the ability to absorb external information and entrepreneurial leadership are also important determinants of technology adoption, as they enable organizations to connect external opportunities with internal transformation (Arifin et al., 2015). This is evident in research by Akbar & Hardiyati (2021) that shows that most of the talent absorption in digital startups in Indonesia is strongly concentrated in areas with high technology adoption capabilities. In the context of these studies, talent capabilities function not only as technical implementers but also as agents of organizational change.

In addition to individual factors, talent management strategies serve as organizational mechanisms that shape the success of technology adoption (Bambang Masudi et al., 2025; Sridar, 2023). Talent management in the digital transformation era focuses not only on recruitment, as in studies by Desty Febrian et al. (2024) dan Hussain et al. (2022), but also on talent development, training, and retention factors relevant to technological needs (Matli & Ngoepe, 2020). Studi oleh Natarajan et al. (2024) shows

that the application of AI in talent management practices, such as AI-based recruitment and predictive analytics, can improve the efficiency and quality of decision-making in organizations adopting new technologies. However, this success is highly dependent on the existence of a systematic strategic framework for integrating technology into the talent management cycle (Ferreira et al., 2024). Without a structured strategy, technology adoption tends to be partial and suboptimal (Sytnik et al., 2024).

From a technical perspective, information technology infrastructure and technology management processes provide the operational prerequisites for adopting new technologies (Alzahrani, 2025; Sirkemaa, 2019). Adequate infrastructure enables efficient technology implementation. However, successful adoption is also determined by the alignment between technological processes and the organization's business objectives. Research by Ahmad et al. (2013) hows that implementing a framework such as the IT Infrastructure Library can improve the effectiveness of technology adoption by aligning IT processes and organizational strategy. Furthermore, Bose & Luo (2012) emphasize that successful technology adoption depends not only on hardware and software but also on the organization's ability to design, implement, and continuously evaluate technological processes. Integrating IT infrastructure with broader business processes, such as the supply chain, has also been shown to strengthen the outcomes of technology implementation (Angeles, 2010).

Beyond internal factors, technology adoption is also influenced by organizational and external environmental factors (Malik et al., 2021; Oyetade & Zuva, 2025). Research by Arifin et al. (2015) identified entrepreneurial leadership, resource availability, knowledge acquisition, and external support as important determinants of technology adoption decisions. Furthermore, network externalities play a significant role in accelerating adoption, where the value of a technology increases with the number of users who adopt it (Katz & Shapiro, 1986). However, technology adoption can also be hampered by negative externalities, such as environmental impacts or social costs, which can lead companies to adopt technology sub optimally without policy intervention (Carbonell-Nicolau, 2024). This broad discourse implies the need for public policy and external stakeholder engagement, which are crucial factors in creating a sustainable and effective technology adoption environment.

Alignment with Theoretical Framework The dominance of talent capabilities over organizational support in this study empirically validates the Resource-Based View (RBV) theory within the context of the digital creative industry. Consistent with RBV, talent capability acts as a "VRIO" resource (Valuable, Rare, Inimitable, and Organized) that provides a unique competitive advantage (Barney, 1991). While TOE framework factors like IT infrastructure and organizational support are necessary foundations, they have become commoditized or "hygiene factors" that are easily accessible to all startups. In contrast, the specialized skill set of workers, their readiness to interact with AI, is a complex, intangible asset that is difficult for competitors to replicate, making it the decisive factor in successful technology adoption.

Table 2 presents the results of data analysis obtained from 226 respondents representing digital startup talent in DKI Jakarta. Respondents had diverse demographic characteristics in terms of gender, age, education level, occupation, and work experience in the digital startup environment. In general, most respondents were of productive age and had secondary to higher education backgrounds, with a predominance of work functions directly related to technology, products, and business development. Respondents had a similar digital technology absorption structure as in the study by Akbar

& Hardiyati (2021) and were in the startup novice player category, which describes startups at a new and developing level (Akbar & Kusnandar, 2024).

Table 2. Respondent Demographic Characteristics (N = 226)

Characteristics	Category	Total (n)	PErcentafe (%)
Gender	Male	132	58,4
	Female	94	41,6
Age	< 25 years	48	21,2
	25–34 years	112	49,6
	35–44 years	52	23
	≥ 45 years	14	6,2
Education	High School	32	14,2
	Diploma	46	20,4
	Bachelor`s Degree	118	52,2
	Postgraduate	30	13,3
Role/Job Position	Technology/IT	76	33,6
	Product & Design	42	18,6
	Marketing & Business	54	23,9
	Operational % Administration	36	15,9
	Management	18	8
Work Experience i	< 1 years	38	16,8
	1–3 years	94	41,6
	4–6 years	62	27,4
	> 6 years	32	14,2

Source: Processed questionnaire data, 2025

The results of the logistic regression analysis, as in Table 2, indicate that the model developed in this study has good performance and is suitable for explaining the probability of AI adoption among digital startup talent in Jakarta. The Likelihood Ratio test shows that the model is statistically significant at the 95 percent confidence level ($p < 0.001$). This limit indicates that the combination of independent variables used simultaneously influences the dependent variable. The Pseudo R^2 (McFadden) value of 0.229 also indicates that the model has sufficient explanatory power to explain variations in AI adoption at the employee level, especially in the context of dynamic and heterogeneous digital startup organizations.

Based on the estimation results as shown in Table 3, talent capability (KT) is the variable with the strongest and most significant influence on AI adoption. This variable has a positive regression coefficient of 2.676 with a significance level of $p < 0.001$. This finding reflects that increasing talent capability significantly increases the likelihood of digital startup workers adopting AI in their daily work activities. The odds ratio value of 14.53 can be interpreted as meaning that workers with higher levels of talent capability

have a more than fourteen times greater chance of adopting AI compared to workers with lower levels of capability.

Statistically, Talent Capability shows a positive and significant influence on AI adoption. This finding reflects the real-world conditions in the digital creative industry in Jakarta, where technology adoption patterns tend to be bottom-up, driven by individual initiative. Workers in the creative sector often adopt generative AI tools (such as ChatGPT or Midjourney) independently to increase personal productivity without waiting for formal instructions from the company. This aligns with the Resource-Based View (RBV) theory, which states that individual knowledge and skills are intangible assets that are key determinants of competitive advantage (Barney, 1991). These results also support research by Oliveira & Martins (2010), which found that employee cognitive and technical readiness are the strongest predictors of new technology acceptance, surpassing other external factors.

Tabel 3. Logistic Regression Results for Artificial Intelligence Adoption

Independent Variable Coefficient	Coefficient (β)	Std. Error	p-value	Odds Ratio
Talent Capability (KT)	2,676	0,543	0	14,53
Talent Management Strategy (MT)	0,04	0,323	0,901	1,04
IT Infrastructure & Processes (ID)	0,569	0,378	0,133	1,77
Organizational Support Factors (FP)	0,046	0,454	0,92	1,05
Constanta	−3,214	0,987	0,001	—

Model Statistics:
Number of observations (N) = 226
Pseudo R^2 (McFadden) = 0.229
Likelihood Ratio χ^2 = significant ($p < 0.001$)

In contrast, talent management (MT) strategies did not demonstrate a statistically significant effect on AI adoption. Although the regression coefficient is positive, the high significance value indicates that the talent management practices measured in this study do not directly influence workers' decisions to adopt AI. This phenomenon can be explained by the characteristics of modern AI technologies, which are largely cloud-based and easily accessible (plug-and-play), thus reducing workers' dependence on heavy physical company infrastructure. In the field, many startup workers use service-based software (SaaS), which does not require complex server installation or formal managerial support. This finding contrasts with the era of adoption of older technologies (such as ERP), which relied heavily on top-down support. This reinforces Li (2020) argument regarding transformation in the creative industries, where the flexibility and accessibility of digital tools allow workers to innovate without the constraints of rigid organizational bureaucracy.

Our finding that talent readiness is crucial aligns with recent studies in the creative industry context. Rossy Yudistira & Eko Wahjudi (2025) found that technology adoption significantly mediates the relationship between entrepreneurial orientation and business performance. However, our study extends this logic by proving that such adoption cannot occur without high-quality human capital. This resonates with Aminah et al. (2021), who

argue that upgrading human resource competencies, specifically in digital entrepreneurship, is the fundamental step before realizing the benefits of digitalization.

Similar results were also found for the information technology (ID) infrastructure and processes variable. This variable had a positive coefficient and odds ratio of 1.77, but was not statistically significant. This finding suggests that the availability of AI-based devices, information systems, and software support does not automatically drive AI adoption among digital startup workers.

Furthermore, organizational support factors (FP) also did not show a significant influence on AI adoption. The relatively small regression coefficient and high significance value indicate that factors such as management commitment, a pro-technology organizational culture, internal policies, and innovative leadership do not directly influence workers' decisions to adopt AI. Overall, the statistical test results in this study indicate that AI adoption among digital startup workers in Jakarta is more influenced by individual factors than organizational factors. Talent capabilities emerged as the primary determinant of AI adoption, while talent management strategy, technology infrastructure, and organizational support factors did not demonstrate statistically significant roles in the model used.

The results of this study indicate that talent capability is a key determinant of artificial intelligence adoption among digital startup workers in Jakarta. These findings generally illustrate the reality that individual readiness, reflected in digital literacy, analytical skills, adaptability, and independence in using technology, plays a crucial role in the AI adoption process. In the context of digital startups with lean organizational structures and flexible work patterns, employees are often key actors in determining whether new technologies can be truly integrated into daily work activities. Therefore, AI adoption depends more on individual capacity than on formal organizational mechanisms.

These findings align with previous studies that emphasize the importance of human resource readiness in adopting digital technology, particularly in organizations with limited resources and high levels of uncertainty (Juhaeni, 2025; Ode et al., 2025). In Indonesia's digital ecosystem, both in MSMEs and startups, advanced technologies such as AI are often available, but their utilization depends heavily on individuals' ability to understand and adapt these technologies to their work needs. Thus, talent capability can be understood as a fundamental prerequisite for enabling AI technology to add value to organizations.

This data also shows that the development of artificial intelligence in Indonesia is still at the individual adoption stage, rather than a concrete strategic initiative by organizations. This fact has two sides. First, adoption naturally grows from the grassroots to boost organizational productivity. This can help organizations solve problems that conventional technology and capabilities may not be able to (Goswami et al., 2023; Vesolovska, 2025). However, on the other hand, this fact has critical consequences: technology development and adoption that are not controlled by a sound strategic plan can alter organizational strategy and planning, leading to disorientation of the organizational structure (Omol, 2024; Palad, 2023).

The insignificant influence of talent management strategies in this study suggests that formal managerial practices do not necessarily have a direct impact on AI adoption at the employee level. This is understandable given that many digital startups are still in their early stages of growth, where human resource policies tend to be informal and adaptive. In such situations, employees' decisions about whether or not to use AI are more

driven by practical needs and personal capabilities than by structured talent management policies (Vesolovska, 2025).

Other discussions from the study also indicate that information technology infrastructure and processes are not yet the primary determinants of AI adoption. This finding indicates that the availability of devices, information systems, and software support does not automatically encourage workers to utilize AI in their work. In the context of digital startups, access to technology is often relatively adequate, so variations in AI adoption are no longer determined solely by technical aspects, but rather by individuals' ability to optimize the technology to support performance.

Another factor supporting this finding is that AI adoption in digital startups is still at an early stage, thus not yet requiring sophisticated technological support. Infrastructure requirements will likely increase with more widespread adoption in the future. This suggests that organizations need to prepare to support future adoption and prevent AI adoption from stalling. Similarly, organizational support factors such as management commitment, a pro-technology organizational culture, and innovative leadership have not shown a direct influence on AI adoption. This may indicate that the influence of organizational factors tends to be indirect and likely operates through the enhancement of individual capabilities. In other words, an organizational environment that supports innovation will effectively encourage AI adoption if accompanied by strengthening employee competencies and readiness.

Overall, the results of this study indicate that the adoption of artificial intelligence among digital startup employees in Jakarta is a bottom-up process, with individual employees being the primary drivers of digital transformation. These findings suggest that technology development strategies in digital startups should prioritize strengthening talent capabilities, while managerial and structural factors play a supporting role, reinforcing, rather than replacing, the role of individuals in the AI adoption process.

CONCLUSIONS AND SUGGESTIONS

This study aims to analyze the factors influencing the adoption of artificial intelligence among digital startup workers in Jakarta, focusing on the role of talent capabilities, talent management strategies, information technology infrastructure and processes, and organizational support factors. Based on the results of a logistic regression analysis, this study found that talent capabilities are the primary determinant of artificial intelligence adoption among digital startup workers.

Empirical findings indicate that workers with higher levels of talent capabilities are significantly more likely to adopt artificial intelligence in their daily work activities. Talent capabilities, including digital literacy, analytical skills, adaptability, resilience, and technological independence, have proven to be key factors enabling the effective use of artificial intelligence technology. Conversely, talent management strategies, information technology infrastructure, and organizational support factors have not shown a statistically significant influence on artificial intelligence adoption.

The results of this study indicate that in the context of digital startups, artificial intelligence adoption is more individual-driven than policy- or organizational-structure-driven. The dynamic and flexible startup work environment makes workers the primary actors in the digital transformation process, while managerial and structural factors play a supporting role, strengthening individual readiness. Therefore, efforts to increase the

adoption of artificial intelligence in digital startups need to prioritize talent capability development as a key foundation.

Overall, this study provides an empirical contribution to the technology adoption literature by highlighting the importance of talent capabilities in driving the adoption of artificial intelligence among digital startup workers in Jakarta. These findings are expected to serve as a reference for startup managers and policymakers in designing more effective and sustainable digital talent development strategies.

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