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# Economic Policy Stability, Digital Governance Capability, and Artificial Intelligence Innovation Performance

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**ABSTRACT**

**Purpose**—This study examines how Economic Policy Stability, Digital Infrastructure Readiness, Research and Development Capability, and Artificial Intelligence Talent Capability influence Artificial Intelligence Innovation Performance. It also assesses the mediating role of Digital Governance Capability in Indonesian manufacturing firms.

**Design/methodology/approach**—This study adopts a quantitative explanatory approach grounded in Real Options Theory, Dynamic Capabilities Theory, National Innovation System Theory, and the Resource-Based View. Data were collected from 250 respondents in Indonesian manufacturing firms and analyzed using Partial Least Squares Structural Equation Modeling with SmartPLS 4.

**Findings**—The results indicate that Economic Policy Stability, Digital Infrastructure Readiness, Research and Development Capability, and Artificial Intelligence Talent Capability each have a positive and significant effect on Artificial Intelligence Innovation Performance. These factors also significantly enhance Digital Governance Capability. Furthermore, Digital Governance Capability positively influences Artificial Intelligence Innovation Performance and partially mediates all proposed relationships.

**Originality/value**—This study advances AI innovation research by integrating policy stability, digital resources, R&D capability, AI talent, and digital governance into a comprehensive model. It highlights Digital Governance Capability as a strategic mechanism that transforms institutional and organizational strengths into AI-driven innovation outcomes.

**Implications**—The findings suggest that manufacturing firms need to strengthen AI innovation not only through technological investment but also through consistent policy support, improved digital infrastructure, enhanced R&D capability, AI talent development, and responsible digital governance.



## 1. Introduction

Artificial intelligence (AI) is now a key driver of industrial change, transforming how companies design products, operate manufacturing systems, optimize supply chains, and develop new business strategies. Recent global data shows AI is no longer limited to experiments or labs but is increasingly integrated into organizational workflows, industrial activities, and innovative processes. The Stanford AI Index Report 2025 highlights AI as a fast-changing technology with significant economic, technical, and societal impacts, while (McKinsey, 2025), a global survey, indicates that organizations are actively redesigning their workflows, governance, and operating models to leverage generative AI. Concurrently, global AI spending is expected to grow substantially, with International Data Corporation (IDC) IDC (2025) projecting worldwide AI expenditure to more than double, reaching about USD 632 billion by 2028. These trends imply that AI has become essential for corporate competitiveness and a country's innovation capacity.

Despite its increasing strategic significance, AI innovation remains highly affected by uncertainty. Developing AI demands long-term investments in digital infrastructure, cloud computing, data management, cybersecurity, R&D capabilities, and specialized human skills. These investments tend to be expensive, path-dependent, and hard to reverse. According to real options theory, companies in uncertain policy environments might delay or reduce irreversible investments because the value of waiting increases when future policy conditions are unstable. This is particularly relevant for AI, where firms need to allocate significant resources before seeing concrete results. The referenced article also highlights that economic policy uncertainty can hinder investment and R&D efforts essential to AI breakthroughs, demonstrating a notable negative impact on AI innovation worldwide.

Increasing research indicates that uncertainty in economic policy can hinder corporate investment, R&D, patent filing, and technological progress. Studies Baker et al. (2016), Bhattacharya et al. (2017), Gulen and Ion (2016), Tajaddini and Gholipour (2021), and William and Fengrong (2022), provide compelling empirical evidence that unstable policy environments discourage firms from investing in long-term innovation. More recent research extends this perspective to AI innovation, analyzing 34 countries from 2017 to 2023 (Ng et al., 2026). It finds that economic policy uncertainty negatively impacts AI innovation, especially in countries with lower innovation capacity. This underscores the need for stable, predictable policy environments to bolster innovation ecosystems and reduce the risks associated with policy shocks.

AI innovation performance cannot be solely attributed to policy stability. It also relies on digital infrastructure readiness, firms' R&D capabilities, and the availability of AI talent. Digital infrastructure underpins AI experimentation, data processing, cloud deployment, and scalable digital operations. R&D capabilities allow firms to turn technological opportunities into new products, processes, and services. AI talent facilitates the absorption, development, and application of AI through technical expertise, data literacy, and cross-functional collaboration. Prior research indicates that AI improves information processing, accelerates knowledge creation, supports business model innovation, and helps firms gain new competitive advantages in complex, data-rich environments.

Beyond organizational and technological skills, digital governance is increasingly seen as key to turning AI resources into innovation results. As AI becomes more integrated into how companies operate, success depends not just on technical preparedness but also on how firms govern data, handle digital risks, comply with regulations, stay transparent, and uphold ethical AI principles. OECD (2024) discusses generative AI and highlights the importance of risk management, accountability, transparency, and governance to ensure that AI adds value while minimizing harm. The European AI policy also stresses the need for trustworthy, human-centric, and well-managed AI systems. These viewpoints indicate that digital governance could act as a strategic link, helping to translate policy stability, infrastructure, R&D, and AI talent into tangible AI innovations.

Previous studies have explored the relationship between policy uncertainty and innovation, but several significant gaps persist. Most research concentrates on broad categories such as green innovation, technological innovation, R&D spending, and patenting, while firm-level artificial intelligence innovation performance, particularly in emerging economies, remains underexplored (Bhattacharya et al., 2017; Cui et al., 2023; Tajaddini and Gholipour, 2021; Zhang et al., 2025). Emerging evidence indicates that economic policy uncertainty can hinder AI innovation, yet discussions are mostly at the cross-country level rather than focusing on individual firms (Ng et al., 2026). Additionally, earlier research primarily assesses the direct effects of policy uncertainty, institutional quality, or government intervention on innovation outcomes, with fewer studies examining how Digital Governance Capability helps turn external stability and internal organizational resources into AI innovation results (Kafka and P. C. Kostis, 2024; Park, 2024; Sharma et al., 2022). Furthermore, Indonesia's manufacturing sector provides meaningful empirical context, as firms are increasingly adopting digitalization, automation, data-driven methods, and AI. Nonetheless, their innovation success heavily relies on institutional stability, infrastructure, R&D capacity, and workforce skills, which are key elements of innovation ecosystem resilience (Fagerberg and Srholec, 2018; Johnson et al., 2022; Mariani et al., 2023).

This study presents an integrated model analyzing how factors such as economic policy stability, digital infrastructure readiness, research and development capability, and artificial intelligence talent capability influence artificial intelligence innovation performance. Digital governance capability functions as a mediating factor. The model draws on four complementary theories: Real Options Theory explains how stable policies reduce uncertainty, encouraging firms to make irreversible AI-related investments (Bernanke, 1983; Dixit and Pindyck, 1994). Dynamic Capabilities Theory describes how firms adapt, integrate, and reconfigure their digital infrastructure, R&D routines, talent resources, and governance capabilities in response to technological changes (Teece et al., 1997). National Innovation System Theory emphasizes the importance of institutional quality, infrastructure, human capital, and knowledge networks in shaping innovation capacity (Fagerberg and Srholec, 2018). Lastly, the Resource-Based View highlights how strategic resources such as AI talent, integrated data systems, R&D capabilities, and digital governance routines serve as valuable, difficult-to-imitate assets that support sustainable innovation performance (Bahoo et al., 2023; Barney, 1991; Igna and Venturini, 2023).

This study makes three key contributions to the existing literature. Firstly, it broadens the policy stability–innovation discussion by focusing specifically on AI innovation performance within the manufacturing sector, rather than on general innovation. Secondly, it introduces digital governance capability as a mediating factor that connects institutional and organizational abilities to AI innovation results. Thirdly, it offers a perspective from an emerging economy by examining Indonesian manufacturing firms, where the interaction of policy stability, digital infrastructure, R&D capability, AI talent, and governance readiness influences AI adoption. These findings aim to provide both theoretical insights for AI innovation research and practical guidance for managers and policymakers who want to enhance the resilience of industrial innovation ecosystems in the digital economy.

## 2. Literature Review

### *2.1 Grand Theoretical Foundation*

This research is based on real options theory, which describes how firms approach strategic investments in the face of uncertainty. According to this theory, when investments are costly, risky, and difficult to reverse, firms tend to postpone or reduce them until future conditions become clearer (Bernanke, 1983; Dixit and Pindyck, 1994). This idea is especially pertinent to artificial intelligence innovation, as AI development demands significant, long-term investments in digital infrastructure, cloud services, data management, cybersecurity, R&D, and specialized talent. In uncertain economic and policy climates, firms may see AI investments as more risky and irreversible, making waiting more attractive. Studies show that economic policy uncertainty can decrease corporate investments, R&D spending, and innovation output because firms become more cautious about long-term innovation investments (Baker et al., 2016; Bhattacharya et al., 2017; Gulen and Ion, 2016; Julio and Yook, 2012; Tajaddini and Gholipour, 2021). Recent data also shows that policy uncertainty negatively affects AI innovation, particularly in countries with weaker innovation capacity, underscoring the importance of policy stability for maintaining thriving AI innovation ecosystems (Ng et al., 2026).

This study draws on dynamic capabilities theory, the national innovation system theory, and the resource-based view. Dynamic Capabilities Theory states that firms need to develop, integrate, and reconfigure internal and external resources to keep pace with rapidly evolving technological environments (Teece et al., 1997). In this context, digital infrastructure readiness, R&D capability, AI talent, and digital governance are seen as dynamic capabilities that help firms adapt to AI-driven changes. The National Innovation System Theory adds that innovation outcomes depend not only on firm resources but also on institutional quality, infrastructure, human capital, and knowledge networks within a national innovation ecosystem (Fagerberg and Srholec, 2018). The resource-based view emphasizes that valuable, rare, inimitable, and non-substitutable resources lead to sustainable competitive advantage (Barney, 1991). Consequently, AI talent, R&D capabilities, integrated data systems, and digital governance routines serve as strategic resources that enhance AI innovation performance. These theories together provide a strong basis for understanding how stable economic policies and organizational capabilities influence AI innovation outcomes through digital governance.

### 2.2 *Determinants of Artificial Intelligence Innovation Performance*

Artificial Intelligence Innovation Performance refers to a company's ability to create AI-driven products, enhance operational processes, improve services, develop new business models, and increase innovation-related competitiveness. Unlike traditional digital innovation, AI innovation requires sophisticated data systems, computing power, specialized talent, R&D investments, and organizational preparedness to turn data technologies into tangible commercial and operational benefits. Studies highlight that AI can accelerate knowledge generation, improve information processing, aid strategic decisions, and reshape innovation pathways (Bahoo et al., 2023; Cockburn et al., 2019; Johnson et al., 2022; Mariani et al., 2023). Consequently, AI innovation performance depends on technological adoption, institutional stability, infrastructure, organizational learning capacity, and the quality of human capital.

Economic Policy Stability is a vital external factor that helps firms make long-term innovation decisions with more confidence. When economic policies are stable, uncertainty around taxation, regulation, investment incentives, and digital transformation is reduced. According to Real Options Theory, firms tend to delay irreversible, high-risk innovation investments when the policy environment is unstable (Bernanke, 1983; Dixit and Pindyck, 1994). Empirical research shows that uncertainty in economic policy decreases corporate investment, R&D spending, and innovation output, as firms become more cautious about allocating resources to long-term projects (Baker et al., 2016; Bhattacharya et al., 2017; Gulen and Ion, 2016; Julio and Yook, 2012; Tajaddini and Gholipour, 2021; Wang et al., 2014). In the AI sector, policy stability is especially critical because AI innovation demands significant investment in data infrastructure, cloud systems, cybersecurity, computing capacity, and skilled labor. Recent studies also suggest that policy uncertainty can heavily limit AI innovation, especially in economies with lower innovation capacity. Therefore, stable economic policies are likely to motivate firms to invest more actively in AI-driven innovation.

Digital infrastructure readiness is a vital factor influencing AI innovation performance. The success of AI-based innovation depends heavily on reliable internet connectivity, cloud services, integrated data systems, cybersecurity, and scalable digital infrastructure. Without sufficient infrastructure, companies may struggle to gather, process, analyze, and deploy data-driven solutions. Existing research emphasizes that AI innovation depends on computational resources, digital platforms, and data ecosystems that help firms automate processes, enhance decision-making, and experiment with new technologies (Johnson et al., 2022; Mariani et al., 2023). Igna and Venturini (2023) also identified infrastructure and digital readiness at the firm level as key determinants of AI innovation across industries. In manufacturing, digital infrastructure supports predictive maintenance, smart production, quality control, supply chain management, and AI-driven product development. Consequently, firms with stronger digital infrastructure are better positioned to transform AI advancements into tangible innovation results.

Research and Development (R&D) capability indicates a company's capacity to allocate resources, experiment, develop knowledge, collaborate externally, and bring new ideas to market. It is vital for innovation because it helps firms spot technological opportunities, absorb external knowledge, and turn scientific insights into new products and processes (Cohen and Levinthal, 1990; Hsu et al., 2014). In AI innovation, R&D capability becomes even more crucial, as companies must test algorithms, create data-driven solutions, assess model performance, and tailor AI applications to specific business needs. Past research shows that R&D investment and innovation skills are closely linked to technological progress and firm-level innovation results (Bhattacharya et al., 2017; Sharma et al., 2022; Tajaddini and Gholipour, 2021). AI also reshapes R&D by supporting both exploration and exploitation, allowing firms to discover new knowledge and improve existing processes (Johnson et al., 2022). Consequently, firms with stronger R&D capabilities are likely to achieve better AI innovation performance.

Artificial intelligence talent capability indicates the availability and quality of employees skilled in AI-related technologies, data literacy, learning agility, and cross-functional teamwork. AI innovation depends heavily on specialized human capital, as developing and deploying AI systems requires expertise in data analytics, machine learning, programming, system integration, and domain-specific problem-solving. The literature indicates that AI talent serves as a strategic resource, supporting firms in developing, adopting, and expanding AI technologies (Huang and Arnold, 2020; Zwetsloot et al., 2021). According to the Resource-Based View, AI talent can be a valuable and hard-to-copy organizational asset that drives sustained innovation performance (Barney, 1991). Additionally, AI innovation extends beyond technical teams; it involves collaboration across engineering, operations, marketing, finance, and management to ensure AI solutions generate business value. Firms with stronger AI talent capabilities are therefore more likely to create AI-powered products, optimize processes, improve services, and develop new business models.

**H1:** Economic Policy Stability positively influences Artificial Intelligence Innovation Performance.

**H2:** Digital Infrastructure Readiness positively influences

Artificial Intelligence Innovation Performance.
**H3:** Research and Development Capability positively influences Artificial Intelligence Innovation Performance.
**H4:** Artificial Intelligence Talent Capability positively influences Artificial Intelligence Innovation Performance.

### *2.3 Drivers of Digital Governance Capability*

Digital Governance Capability refers to a company's capacity to establish clear rules, structures, and mechanisms for managing digital data, implementing ethical AI, complying with regulations, ensuring transparency, and managing technology risks. In AI-driven innovation ecosystems, effective digital governance is vital because companies must handle data responsibly: collecting, processing, sharing, and using it appropriately. Economic policy stability can enhance Digital Governance Capability by reducing regulatory uncertainty and motivating firms to adopt more predictable governance frameworks for digital transformation. When economic, digital, tax, and investment policies are stable, companies are more likely to formalize data governance, comply with AI-related rules, and invest in long-term digital risk strategies. This perspective aligns with institutional and innovation research showing that stable policy environments promote investment in innovation, reduce uncertainty, and strengthen organizational confidence in the development of governance capabilities (Baker et al., 2016; Bhattacharya et al., 2017; Gulen and Ion, 2016; Park, 2024). Recent AI innovation studies also indicate that policy uncertainty can hinder AI progress, as AI relies on regulatory clarity, infrastructure investments, and long-term organizational commitment.

Digital infrastructure readiness, research and development (R&D) capability, and AI Talent are key drivers of digital governance. Firms with robust digital infrastructure can more effectively develop integrated data systems, secure cloud services, cybersecurity measures, and scalable platforms that support governance. R&D enables experimentation with new technologies and the development of routines for risk assessment, ethical considerations, and knowledge-based decision-making. AI talent provides the technical expertise to implement responsible AI, improve data literacy, monitor algorithmic risks, and facilitate cross-functional governance. These points align with Dynamic Capabilities Theory, which emphasizes a firm's ability to adapt and reconfigure resources in changing technology environments Teece et al. (1997), and are supported by AI governance research that underscores ethics, transparency, compliance, and risk management in AI deployment (Kaplan and Haenlein, 2020; Morley et al., 2020; OECD, 2024).
**H5:** Economic Policy Stability has a positive effect on Digital Governance Capability.
**H6:** Digital Infrastructure Readiness positively impacts Digital Governance Capability.
**H7:** Research and Development Capability enhances Digital Governance Capability.
**H8:** Artificial Intelligence Talent Capability positively contributes to Digital Governance Capability.

### *2.4 Digital Governance Capability and Artificial Intelligence Innovation Performance*

Digital Governance Capability is vital for improving AI Innovation Performance in organizations. Effective AI-driven innovation depends not only on technological tools but also on responsible management of data, ethics, compliance, transparency, and digital risks. Organizations with strong digital governance are better able to transform AI resources into reliable products, efficient processes, better services, and innovative business models. Governance frameworks help reduce uncertainty, foster stakeholder trust, and ensure AI applications adhere to regulatory and ethical standards. Research shows that AI governance, ethics, transparency, and risk management are key to turning AI's technical potential into real organizational benefits (Kaplan and Haenlein, 2020; Morley et al., 2020; OECD, 2024). Additionally, studies suggest that effective AI implementation can enhance knowledge creation, operational efficiency, and business model innovation, provided organizations have the right capabilities and governance structures (Bahoo et al., 2023; Johnson et al., 2022; Mariani et al., 2023). Therefore, strengthening Digital Governance Capability is likely to increase a firm's AI Innovation Performance.
**H9:** Digital Governance Capability positively influences Artificial Intelligence Innovation Performance.

### *2.5 Mediating Role of Digital Governance Capability*

Digital Governance Capability serves as a strategic bridge, showing how institutional stability and organizational resources translate into success in Artificial Intelligence Innovation Performance. Economic Policy Stability fosters a more predictable environment, motivating companies to invest in data governance, regulatory compliance, AI risk management, and transparent digital decision-making. These governance practices help firms reduce uncertainty, strengthen stakeholder trust, and translate AI investments into innovative outcomes. This aligns with Real Options Theory, which holds that policy stability reduces the incentive to delay irreversible innovation investments. It also supports earlier research indicating that policy uncertainty hampers corporate investment, R&D, and technological innovation (Bernanke, 1983; Bhattacharya et al., 2017; Dixit and Pindyck, 1994; Gulen and Ion, 2016). Recent studies further show that policy uncertainty can significantly limit AI innovation, as AI development depends on long-term investments, clear regulations, and dependable governance frameworks (Ng et al., 2026).

Digital Governance Capability shapes how Digital Infrastructure Readiness, R&D Capability, and AI Talent Capability influence AI Innovation Performance. While digital infrastructure provides the essential technical foundation for secure data systems, cloud computing, cybersecurity, and scalable AI deployment, effective governance through clear rules and risk management enhances these resources' capacity to foster innovation. R&D supports experimentation and knowledge generation, but digital governance ensures that these processes comply with ethical, legal, and organizational standards. AI talent enables the development and application of AI technologies, yet its impact on innovation depends on governance practices that manage technical expertise, data responsibility, algorithmic transparency, and cross-functional teamwork. Ultimately, digital governance capability serves as a bridge, transforming technological, knowledge, and human resources into responsible, market-ready AI innovations (Bahoo et al., 2023; Johnson et al., 2022; Mariani et al., 2023; Morley et al., 2020; OECD, 2024; Teece et al., 1997).
**H10:** Digital Governance Capability mediates the relationship

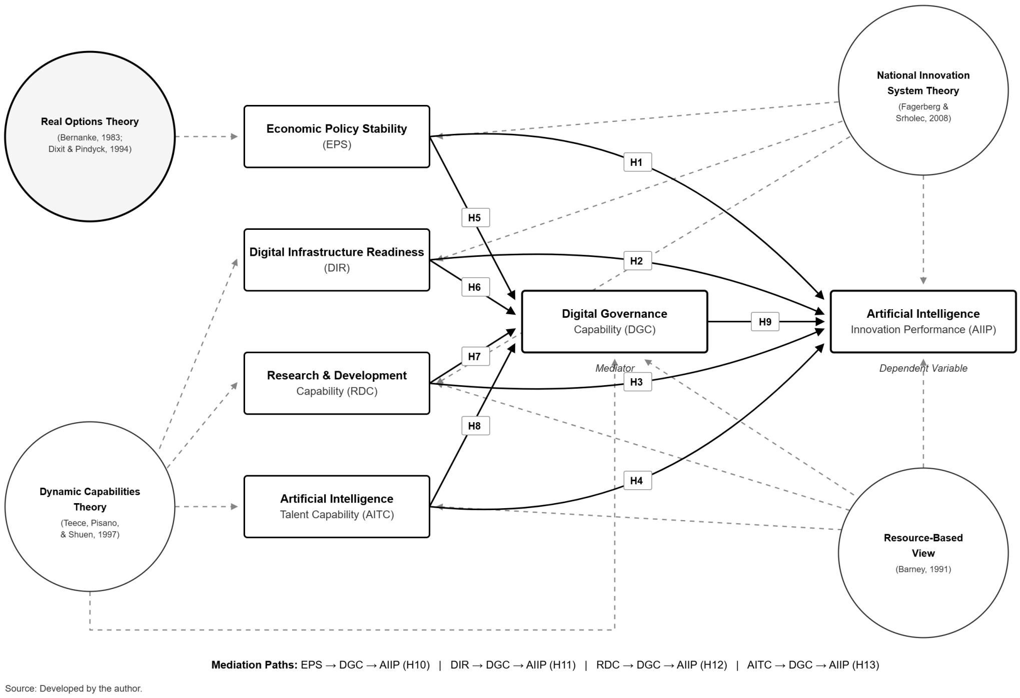


**Fig. 1.** Conceptual Framework

between Economic Policy Stability and Artificial Intelligence Innovation Performance.

**H11:** Digital Governance Capability mediates the relationship between Digital Infrastructure Readiness and Artificial Intelligence Innovation Performance.

**H12:** Digital Governance Capability mediates the relationship between Research and Development Capability and Artificial Intelligence Innovation Performance.

**H13:** Digital Governance Capability mediates the relationship between Artificial Intelligence Talent Capability and Artificial Intelligence Innovation Performance.

### *2.6 Conceptual Framework*

Building on the theoretical foundation and hypothesis development, this study presents an integrated conceptual framework that explains how factors such as Economic Policy Stability, Digital Infrastructure Readiness, Research and Development Capability, and Artificial Intelligence Talent capability influence the performance of artificial intelligence innovation. These effects are both direct and indirect, mediated by digital governance capability. The framework treats digital governance capability as a mediator that transforms institutional stability, digital infrastructure, R&D capacity, and AI-related human capital into improved AI products, processes, services, business models, and competitive innovations. The relationships among these constructs are depicted in Figure 1.

## 3. Research Methodology

### *3.1 Research Design*

This study employs a quantitative research design with an explanatory approach to analyze the direct and mediating effects among variables, including Economic Policy Stability, Digital Infrastructure Readiness, Research and Development Capability, Artificial Intelligence Talent Capability, Digital Governance Capability, and Artificial Intelligence Innovation Performance. The quantitative method is suitable because the research aims to test theoretically derived hypotheses and quantify causal connections among latent constructs through structured survey data. The research model is based on real options theory, which describes how policy stability reduces uncertainty in irreversible AI investments, and is supported by dynamic capabilities theory, explaining how firms develop and reconfigure digital, R&D, talent, and governance capabilities to enhance innovation performance (Bernanke, 1983; Dixit and Pindyck, 1994; Teece et al., 1997). Data were gathered through a structured questionnaire employing a five-point Likert scale and analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM), an appropriate technique for predictive research, complex models with many constructs, mediation analysis, and moderate sample sizes common in management and innovation research (Hair, Tomas, et al., 2017; Sarstedt, Radomir, et al., 2022).

### *3.2 Research Object and Sample*

This study focuses on Indonesian manufacturing firms that have started integrating artificial intelligence and digital technologies into their operations, production, services, or management. The analysis targets individual employees, supervisors, managers, and decision-makers who possess sufficient knowledge of digital transformation, AI adoption, R&D activities, digital governance, and innovation practices within their companies. The manufacturing sector is chosen because it is a key industry where AI can improve productivity, process efficiency, quality control, predictive maintenance, supply chain management, and business model innovation. The sample includes 250 respondents, deemed sufficient for PLS-SEM analysis considering the model's multiple latent variables, reflective indicators, and mediation paths (Hair, Tomas, et al.,

**Table 1.** **Research Object and Sample Design**

| Parameter | Description | Justification |
|---|---|---|
| Research location | Indonesia | Emerging digital economy |
| Industrial sector | Manufacturing firms | Relevant for AI adoption |
| Research object | Firms adopting AI and digital systems | Fits the research focus |
| Unit of analysis | Individual respondents | Captures firm-level perceptions |
| Respondent criteria | Employees, supervisors, managers, decision-makers | Relevant organizational knowledge |
| Sample size | 250 respondents | Adequate for PLS-SEM analysis |
| Sampling technique | Purposive sampling | Based on respondent relevance |
| Data collection | Structured questionnaire | Standardized measurement procedure |
| Measurement scale | Five-point Likert scale | 1 = strongly disagree; 5 = strongly agree |
| Data analysis | SmartPLS 4 | PLS-SEM analysis |

**Table 2.** **Operational Definition of Variables and Measurement Indicators**

| Variable | Dimension | Indicator Item | Source |
|---|---|---|---|
| Economic Policy Stability (EPS) | Policy predictability | Economic policies are predictable for business decisions. | (Baker et al., 2016; Gulen and Ion, 2016) |
| | Regulatory clarity | Digital regulations support innovation activities. | (Bhattacharya et al., 2017; Cui et al., 2023) |
| | Tax consistency | Tax policies do not hinder technology investment. | (Dwivedi et al., 2022; Wang et al., 2014) |
| | Investment certainty | Firms feel secure investing in AI technologies. | (Julio and Yook, 2012; Tian et al., 2022) |
| | Policy coordination | Government policies are consistent across institutions. | (Kafka and P. C. Kostis, 2024; Park, 2024) |
| Digital Infrastructure Readiness (DIR) | Connectivity | Internet infrastructure supports digital operations. | (Johnson et al., 2022; Mariani et al., 2023) |
| | Cloud readiness | Firms have access to cloud computing resources. | (HAI, 2025; OECD, 2024) |
| | Data system | Data systems are integrated across business functions. | (Akram et al., 2024; Morley et al., 2020) |
| | Cybersecurity | Digital infrastructure is protected from cyber risks. | (European Commission, 2025; OECD, 2024) |
| | Scalability | Digital infrastructure supports AI expansion. | (Bahoo et al., 2023; Igna and Venturini, 2023) |
| Research and Development Capability (RDC) | R&D intensity | Firms allocate sufficient budget for R&D activities. | (Bhattacharya et al., 2017; Hsu et al., 2014) |
| | Experimentation | Firms actively experiment with new technologies. | (Mariani et al., 2023; Teece et al., 1997) |
| | Knowledge creation | Firms generate new knowledge for innovation. | (Cohen and Levinthal, 1990; Fagerberg and Srholec, 2018) |
| | Collaboration | Firms collaborate with external partners in innovation. | (Lim et al., 2018; Qureshi et al., 2021) |
| | Commercialisation | R&D outcomes are directed toward new products or processes. | (Neves et al., 2021; Sharma et al., 2022) |
| Artificial Intelligence Talent Capability (AITC) | Technical skill | Employees possess technical skills related to AI. | (Huang and Arnold, 2020; Zwetsloot et al., 2021) |
| | Data literacy | Employees are able to understand and use digital data. | (McKinsey, 2025; Morley et al., 2020) |
| | Learning capability | Firms support AI-related training and learning. | (Bahoo et al., 2023; Mariani et al., 2023) |
| | Talent retention | Firms are able to retain digital and AI talent. | (Igna and Venturini, 2023; Johnson et al., 2022) |
| | Cross-functional skill | Cross-functional teams are involved in AI projects. | (Åström et al., 2022; A. Kostis and Ritala, 2020) |
| Digital Governance Capability (DGC) | Data governance | Firms have clear rules for data governance. | (European Commission, 2025; OECD, 2024) |
| | Ethical AI | AI implementation considers ethical principles. | (Haenlein and Kaplan, 2019; Morley et al., 2020) |
| | Compliance | Firms comply with digital and AI-related regulations. | (Kafka and P. C. Kostis, 2024; Park, 2024) |
| | Transparency | Digital decision-making processes are transparent. | (Kaplan and Haenlein, 2020; OECD, 2024) |
| | Risk management | AI-related risks are managed systematically. | (Akram et al., 2024; Tursunbayeva et al., 2024) |
| Artificial Intelligence Innovation Performance (AIIP) | Product innovation | Firms develop AI-based products. | (Bahoo et al., 2023; Cockburn et al., 2019) |
| | Process innovation | AI improves operational processes. | (Johnson et al., 2022; Mariani et al., 2023) |
| | Service innovation | AI improves customer service quality. | (Haenlein and Kaplan, 2019; McKinsey, 2025) |
| | Business model innovation | AI encourages new business models. | (Åström et al., 2022; A. Kostis and Ritala, 2020) |
| | Competitive innovation | AI improves innovation-based competitiveness. | (Gonzales, 2023; HAI, 2025) |

2017; Sarstedt, Ringle, et al., 2017).

### 3.3 *Operational Definition of Variables*

This study used a measurement instrument designed to operationalize six hidden variables: Economic Policy Stability, Digital Infrastructure Readiness, Research and Development Capability, Artificial Intelligence Talent Capability, Digital Governance Capability, and Artificial Intelligence Innovation Performance. Each variable is assessed using five reflective indicators drawn from established research on topics such as economic policy uncertainty, digital innovation, AI innovation, dynamic capabilities, and digital governance. Reflective indicators are suitable because each item reflects the underlying concept and should correlate with other indicators of the same variable. All items are rated on a five-point Likert scale from 1 (strongly disagree) to 5 (strongly agree). This format, common in management, innovation, and information systems research, measures perceptions of organizational conditions and capabilities (Sarstedt, Radomir, et al., 2022).

The variables' operationalization relies on relevant literature. Economic policy stability is derived from studies on policy uncertainty and investment, emphasizing factors such as predictability, regulatory clarity, tax consistency, investment certainty, and policy coordination as vital to innovation (Baker et al., 2016; Bhattacharya et al., 2017; Gulen and Ion, 2016). Digital Infrastructure Readiness, R&D Capability, and AI Talent Capability are based on research related to AI innovation, digital transformation, R&D, and human capital (Bahoo et al., 2023; Igna and Venturini, 2023; Johnson et al., 2022; Mariani et al., 2023). Digital Governance Capability assesses data governance, ethical AI, compliance, transparency, and risk management, highlighting the growing importance of responsible AI deployment (Kaplan and Haenlein, 2020; Morley et al., 2020; OECD, 2024). Artificial intelligence innovation performance is measured through AI-based products, processes, services, business models, and competitive innovations. The complete operational definitions, dimensions, measurement indicators, and supporting sources are presented in Table 2.

### 3.4 *Data Collection Procedure*

Data for this study were gathered through a structured survey distributed to employees, supervisors, managers, senior managers, and decision-makers in Indonesian manufacturing firms that have started adopting artificial intelligence and digital technologies. The questionnaire uses a five-point Likert scale from 1 = strongly disagree to 5 = strongly agree and includes items measuring Economic Policy Stability, Digital Infrastructure Readiness, Research and Development Capability, Artificial Intelligence Talent Capability, Digital Governance Capability, and Artificial Intelligence Innovation Performance.

Before full deployment, the instrument should be reviewed for clarity, content validity, and relevance to the manufacturing context. Survey-based data collection is suitable for exploring organizational perceptions and latent constructs in innovation and management research, especially when testing theoretically developed relationships among variables (Hair, Hult, et al., 2021; Sarstedt, Radomir, et al., 2022). To minimize response bias, respondents are informed that their data will be used for academic purposes only and that responses will remain confidential.

### 3.5 Data Analysis Technique

The data are analyzed with Partial Least Squares Structural Equation Modeling (PLS-SEM) in SmartPLS 4 because the research model includes multiple latent variables, reflective indicators, direct effects, and mediation relationships. PLS-SEM is suitable for predictive and explanatory research, particularly for complex models, non-normal data, and moderate sample sizes (Hair, Hult, et al., 2021; Sarstedt, Radomir, et al., 2022). The analysis proceeds in two main stages. First, the measurement model is evaluated by examining indicator reliability, internal consistency, convergent validity, and discriminant validity using outer loadings, Cronbach's alpha, composite reliability, average variance extracted, the Fornell-Larcker criterion, cross-loadings, and the heterotrait-monotrait ratio. Next, the structural model is assessed through collinearity statistics, path coefficients, R-squared, effect size, predictive relevance, and bootstrapping to test the direct and indirect hypotheses, including the mediating role of digital governance capability.

## 4. Results and Discussion

### 4.1 Respondent Demographic Profile

The respondent demographic profile offers an overview of the sample characteristics in this study. A total of 250 participants from Indonesian manufacturing firms took part in the survey. The gender distribution was fairly balanced, with 52.8% male and 47.2% female. Most respondents were aged 31-40 years (38.0%), followed by those aged 21-30 years (32.0%), showing the sample mainly consisted of active, working-age employees. Regarding education, the majority possessed a diploma or bachelor's degree (65.6%), indicating an adequate educational background to understand the research tools. In terms of work experience, most had 2–5 years (48.0%), with 30.0% having more than 5 years. Overall, the demographic profile suggests that the respondents are well-suited to evaluate digital transformation, AI adoption, digital governance capability, and innovation performance in manufacturing firms. The detailed respondent profile is available in Table 3.

### 4.2 Descriptive Statistical Analysis

A descriptive statistical analysis was conducted to examine the central tendency and variability of the research variables. As shown in Table 4, all constructs had mean scores above the midpoint of the five-point Likert scale, indicating that respondents generally perceived the variables from moderate to high levels. Economic Policy Stability (EPS) recorded the highest average (M = 3.593; SD = 0.975), implying that participants viewed policy predictability, regulatory clarity, tax consistency, investment assurance, and policy coordination as

**Table 3. Respondent Demographic Profile**

| Characteristic | Category | Freq. | % |
|---|---|---|---|
| Gender | Male | 132 | 52.80 |
| | Female | 118 | 47.20 |
| Age | 21–30 years | 80 | 32.00 |
| | 31–40 years | 95 | 38.00 |
| | 41–50 years | 52 | 20.80 |
| | >50 years | 23 | 9.20 |
| Education | Senior High School | 58 | 23.20 |
| | Diploma/Bachelor | 164 | 65.60 |
| | Master Degree | 28 | 11.20 |
| Experience | <2 years | 55 | 22.00 |
| | 2–5 years | 120 | 48.00 |
| | >5 years | 75 | 30.00 |
| Total | | 250 | 100.00 |

**Table 4. Descriptive Statistics of Research Variables**

| Var. | N | Mean | SD | Min. | Max. |
|---|---|---|---|---|---|
| EPS | 250 | 3.593 | 0.975 | 1.000 | 5.000 |
| DIR | 250 | 3.557 | 0.982 | 1.000 | 5.000 |
| RDC | 250 | 3.544 | 0.986 | 1.000 | 5.000 |
| AITC | 250 | 3.562 | 0.975 | 1.200 | 5.000 |
| DGC | 250 | 3.460 | 1.062 | 1.000 | 5.000 |
| AIIP | 250 | 3.518 | 1.057 | 1.200 | 5.000 |

relatively supportive of AI-related innovation. Next, Artificial Intelligence Talent Capability (AITC) (M = 3.562; SD = 0.975) and Digital Infrastructure Readiness (DIR) (M = 3.557; SD = 0.982) suggest that firms possess fairly favorable human capital and infrastructure conditions for AI adoption. Research and Development Capability (RDC) also showed a positive trend (M = 3.544; SD = 0.986), highlighting the importance of experimentation, knowledge creation, collaboration, and commercialization in boosting innovation. Meanwhile, Artificial Intelligence Innovation Performance (AIIP) had a mean of 3.518 with a standard deviation of 1.057, indicating that AI-related outcomes—products, processes, services, business models, and competitive advances—are viewed as moderately strong. The lowest mean was for Digital Governance Capability (DGC) (M = 3.460; SD = 1.062), suggesting governance areas such as data management, ethical AI, compliance, transparency, and risk oversight need further development. Overall, these descriptive findings indicate that Indonesian manufacturing firms generally have a high level of readiness and capacity for AI innovation, though digital governance remains an area for improvement.

### 4.3 Measurement Model Evaluation

The measurement model was analyzed to assess how well the reflective indicators represent each latent construct within the research framework. As shown in Figure 2, the model includes six reflective constructs: Economic Policy Stability (EPS), Digital Infrastructure Readiness (DIR), Research and Development Capability (RDC), Artificial Intelligence Talent Capability (AITC), Digital Governance Capability (DGC), and Artificial Intelligence Innovation Performance (AIIP). The figure shows that all indicators are strongly linked to their respective constructs, with outer loadings above the minimum recommended threshold. This suggests that the measurement

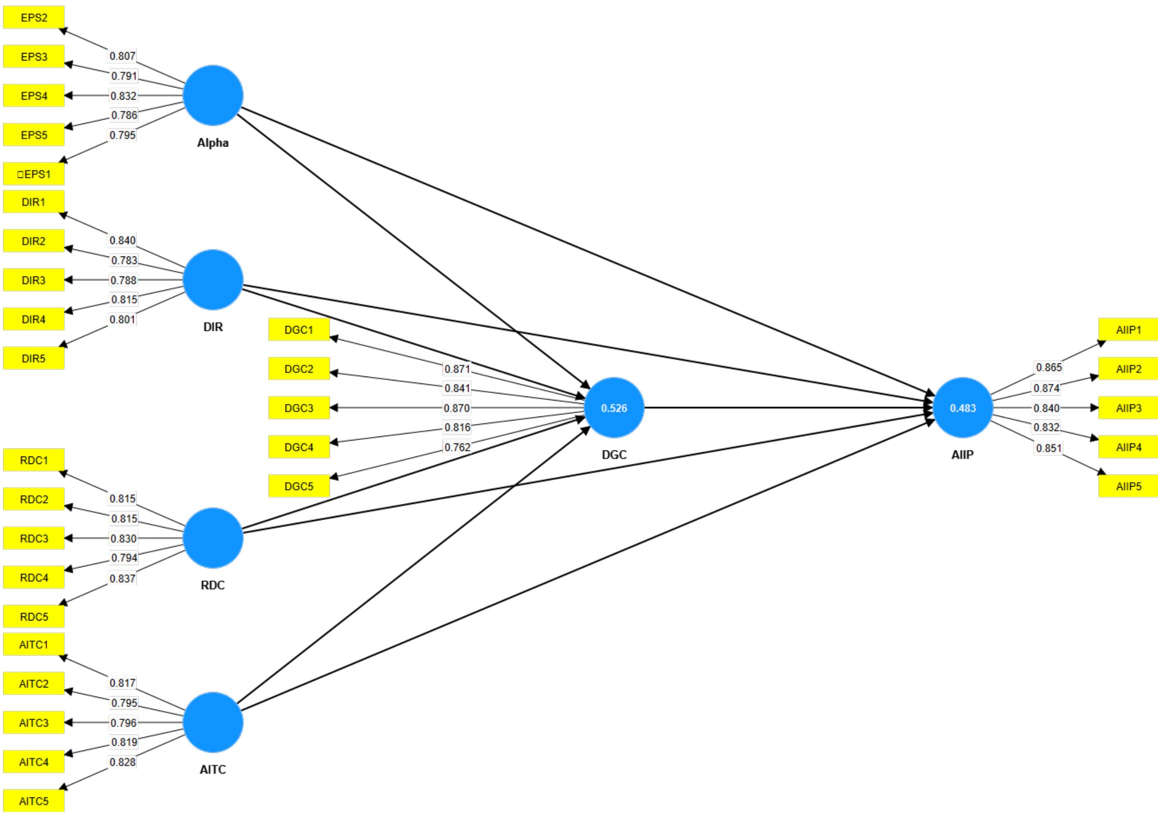


**Fig. 2.** Measurement Model Results

structure is statistically sound and that the indicators effectively measure their intended constructs. Consequently, Figure 2 visually affirms the robustness of the reflective measurement model prior to conducting further reliability and validity tests.

The evaluation of the measurement model included checks for indicator reliability, internal consistency, convergent validity, and discriminant validity. Following standard PLS-SEM practices, outer loadings should generally be above 0.7000, Cronbach's alpha and composite reliability should exceed 0.7000, the Average Variance Extracted (AVE) should be above 0.5000, and the HTMT should remain below the conservative cutoff of 0.8500. These benchmarks are broadly accepted as evidence that the measurement indicators are both statistically reliable and conceptually valid for their respective constructs. The detailed results are summarized in Tables 5–9, which display outer loadings, construct reliability, convergent validity, the Fornell–Larcker criterion, cross-loadings, and HTMT.

Table 5 indicates that all measurement indicators have outer loading values exceeding the recommended threshold of 0.7000, ranging from 0.7620 to 0.8740. The highest loading was for AIIP2 at 0.8740, showing it has the greatest contribution to measuring Artificial Intelligence Innovation Performance. The lowest was DGC5 at 0.7620, which still exceeds the minimum acceptable threshold. The AIIP indicators ranged from 0.8320 to 0.8740; AITC from 0.7950 to 0.8280; DGC from 0.7620 to 0.8710; DIR from 0.7830 to 0.8400; EPS from 0.7860 to 0.8320; and RDC from 0.7940 to 0.8370. These results confirm that all indicators demonstrate sufficient reliability and are suitable for measuring their respective constructs. Consequently, no indicators were eliminated from the measurement model.

Table 6 shows that the results for construct reliability and convergent validity meet the established PLS-SEM standards. Cronbach's alpha values ranged from 0.8620 to 0.9060, all above the minimum threshold of 0.7000, indicating strong internal consistency for each construct. The highest alpha was 0.9060 for Artificial Intelligence Innovation Performance, and the lowest was 0.8620 for Economic Policy Stability, both indicating reliable measurements. Composite reliability rho_c values were between 0.9000 and 0.9300, confirming robust reliability across all constructs. AVE values varied from 0.6440 to 0.7270, well above the 0.5000 cutoff, showing that each construct accounts for more than half of the variance in its indicators. Overall, these results demonstrate adequate internal consistency, reliability, and convergent validity for all constructs.

As demonstrated in Table 7, discriminant validity was initially assessed using the Fornell–Larcker criterion. The findings show that the square root of AVE for each construct, indicated on the diagonal, is greater than its correlations with other constructs. For example, Artificial Intelligence Innovation Performance has a diagonal value of 0.8520, surpassing its correlations with AITC (0.4410), EPS (0.4170), DGC (0.5790), DIR (0.4530), and RDC (0.5100). Similarly, Digital Governance Capability has a diagonal value of 0.8330, which exceeds its correlations with AIIP, AITC, EPS, DIR, and RDC. This trend is consistent across all other constructs, including AITC, EPS, DIR, and RDC. These results confirm that each construct explains more variance in its indicators than in those of others, supporting the empirical validity of the constructs according to the Fornell–Larcker criterion.

The cross-loading results in Table 8 further confirm discriminant validity. Each indicator mainly loaded on its respective construct, with lower loadings on others. For example, the indicators of Artificial Intelligence Innovation Performance had strong loadings on AIIP, ranging from 0.8320 to 0.8740, with lower loadings elsewhere. Similarly, all AITC indicators loaded most strongly on AITC, with values from 0.7950 to

**Table 5.** **Outer Loadings of Measurement Indicators**

| Construct | Indicator | Outer Loading | Result |
|---|---|---|---|
| Artificial Intelligence Innovation Performance (AIIP) | AIIP1 | 0.8650 | Valid |
| | AIIP2 | 0.8740 | Valid |
| | AIIP3 | 0.8400 | Valid |
| | AIIP4 | 0.8320 | Valid |
| | AIIP5 | 0.8510 | Valid |
| Artificial Intelligence Talent Capability (AITC) | AITC1 | 0.8170 | Valid |
| | AITC2 | 0.7950 | Valid |
| | AITC3 | 0.7960 | Valid |
| | AITC4 | 0.8190 | Valid |
| | AITC5 | 0.8280 | Valid |
| Digital Governance Capability (DGC) | DGC1 | 0.8710 | Valid |
| | DGC2 | 0.8410 | Valid |
| | DGC3 | 0.8700 | Valid |
| | DGC4 | 0.8160 | Valid |
| | DGC5 | 0.7620 | Valid |
| Digital Infrastructure Readiness (DIR) | DIR1 | 0.8400 | Valid |
| | DIR2 | 0.7830 | Valid |
| | DIR3 | 0.7880 | Valid |
| | DIR4 | 0.8150 | Valid |
| | DIR5 | 0.8010 | Valid |
| Economic Policy Stability (EPS) | EPS1 | 0.7950 | Valid |
| | EPS2 | 0.8070 | Valid |
| | EPS3 | 0.7910 | Valid |
| | EPS4 | 0.8320 | Valid |
| | EPS5 | 0.7860 | Valid |
| Research and Development Capability (RDC) | RDC1 | 0.8150 | Valid |
| | RDC2 | 0.8150 | Valid |
| | RDC3 | 0.8300 | Valid |
| | RDC4 | 0.7940 | Valid |
| | RDC5 | 0.8370 | Valid |

**Table 6.** **Construct Reliability and Convergent Validity**

| Construct | Cronbach's Alpha | rho_a | rho_c | AVE | Result |
|---|---|---|---|---|---|
| AIIP | 0.9060 | 0.9070 | 0.9300 | 0.7270 | Reliable and valid |
| AITC | 0.8700 | 0.8730 | 0.9060 | 0.6580 | Reliable and valid |
| EPS | 0.8620 | 0.8650 | 0.9000 | 0.6440 | Reliable and valid |
| DGC | 0.8890 | 0.8980 | 0.9190 | 0.6940 | Reliable and valid |
| DIR | 0.8650 | 0.8700 | 0.9020 | 0.6490 | Reliable and valid |
| RDC | 0.8770 | 0.8790 | 0.9100 | 0.6700 | Reliable and valid |

**Table 7.** **Fornell–Larcker Criterion**

| Construct | AIIP | AITC | EPS | DGC | DIR | RDC |
|---|---|---|---|---|---|---|
| AIIP | 0.8520 | | | | | |
| AITC | 0.4410 | 0.8110 | | | | |
| EPS | 0.4170 | 0.2420 | 0.8020 | | | |
| DGC | 0.5790 | 0.3980 | 0.5070 | 0.8330 | | |
| DIR | 0.4530 | 0.2400 | 0.2430 | 0.5430 | 0.8050 | |
| RDC | 0.5100 | 0.2750 | 0.2410 | 0.4720 | 0.3640 | 0.8180 |

0.8280. Indicators for DGC, DIR, EPS, and RDC also showed their highest loadings on their respective constructs. This pattern shows each measurement item correlates more closely with its intended latent variable than with others. Therefore, the cross-loadings support the discriminant validity of the measurement model and confirm that the indicators align both conceptually and statistically with their constructs.

Table 9 shows that the Heterotrait–Monotrait Ratio provides a stricter test of discriminant validity. All HTMT values are below the conservative threshold of 0.8500, confirming that the constructs are clearly distinct. The highest HTMT value, 0.6410, is between Digital Governance Capability and Artificial Intelligence Innovation Performance, which is comfortably below the cutoff. Other HTMT values, from 0.2710 to 0.6080, indicate that the correlations among constructs are not overly high. These results suggest limited conceptual overlap among the constructs in the measurement model. Together with the Fornell–Larcker criterion and cross-loadings, the HTMT findings strongly support the discriminant validity of the model. Therefore, the measurement model is considered reliable, valid,

**Table 8.** **Cross-Loadings**

| Indicator | AIIP | AITC | EPS | DGC | DIR | RDC |
|---|---|---|---|---|---|---|
| AIIP1 | 0.8650 | 0.4080 | 0.3390 | 0.4900 | 0.3890 | 0.4650 |
| AIIP2 | 0.8740 | 0.3530 | 0.3710 | 0.5240 | 0.3960 | 0.4740 |
| AIIP3 | 0.8400 | 0.3550 | 0.3490 | 0.4610 | 0.4040 | 0.4310 |
| AIIP4 | 0.8320 | 0.3490 | 0.3240 | 0.4840 | 0.3910 | 0.3570 |
| AIIP5 | 0.8510 | 0.4110 | 0.3920 | 0.5050 | 0.3540 | 0.4390 |
| AITC1 | 0.3070 | 0.8170 | 0.1760 | 0.3140 | 0.1810 | 0.2150 |
| AITC2 | 0.3440 | 0.7950 | 0.1940 | 0.3320 | 0.1650 | 0.2060 |
| AITC3 | 0.3470 | 0.7960 | 0.2030 | 0.2860 | 0.1440 | 0.2150 |
| AITC4 | 0.3970 | 0.8190 | 0.2340 | 0.3770 | 0.2490 | 0.2020 |
| AITC5 | 0.3820 | 0.8280 | 0.1660 | 0.2960 | 0.2200 | 0.2770 |
| DGC1 | 0.5310 | 0.3920 | 0.4490 | 0.8710 | 0.5080 | 0.4290 |
| DGC2 | 0.4770 | 0.3130 | 0.4180 | 0.8410 | 0.5000 | 0.4230 |
| DGC3 | 0.5250 | 0.4010 | 0.4540 | 0.8700 | 0.4850 | 0.4350 |
| DGC4 | 0.4450 | 0.2750 | 0.4260 | 0.8160 | 0.4130 | 0.3410 |
| DGC5 | 0.4170 | 0.2520 | 0.3550 | 0.7620 | 0.3300 | 0.3210 |
| DIR1 | 0.4150 | 0.2280 | 0.2510 | 0.5150 | 0.8400 | 0.3220 |
| DIR2 | 0.3570 | 0.1630 | 0.1510 | 0.3950 | 0.7830 | 0.3160 |
| DIR3 | 0.3750 | 0.1550 | 0.2420 | 0.4220 | 0.7880 | 0.2390 |
| DIR4 | 0.3230 | 0.2130 | 0.2040 | 0.4350 | 0.8150 | 0.3180 |
| DIR5 | 0.3470 | 0.2020 | 0.1160 | 0.4050 | 0.8010 | 0.2700 |
| EPS1 | 0.3210 | 0.2150 | 0.7950 | 0.4310 | 0.2090 | 0.1940 |
| EPS2 | 0.3060 | 0.1650 | 0.8070 | 0.3990 | 0.2110 | 0.1820 |
| EPS3 | 0.3640 | 0.1770 | 0.7910 | 0.4240 | 0.2020 | 0.1700 |
| EPS4 | 0.3690 | 0.1870 | 0.8320 | 0.4380 | 0.2060 | 0.2420 |
| EPS5 | 0.3050 | 0.2320 | 0.7860 | 0.3250 | 0.1380 | 0.1740 |
| RDC1 | 0.3870 | 0.2090 | 0.1490 | 0.3350 | 0.3370 | 0.8150 |
| RDC2 | 0.4500 | 0.1620 | 0.2310 | 0.4060 | 0.3160 | 0.8150 |
| RDC3 | 0.4050 | 0.2550 | 0.2280 | 0.3620 | 0.2510 | 0.8300 |
| RDC4 | 0.4070 | 0.2480 | 0.1630 | 0.3900 | 0.3360 | 0.7940 |
| RDC5 | 0.4310 | 0.2520 | 0.2080 | 0.4290 | 0.2550 | 0.8370 |

**Table 9.** **Heterotrait–Monotrait Ratio**

| Construct | AIIP | AITC | EPS | DGC | DIR | RDC |
|---|---|---|---|---|---|---|
| AIIP | | | | | | |
| AITC | 0.4930 | | | | | |
| EPS | 0.4690 | 0.2790 | | | | |
| DGC | 0.6410 | 0.4430 | 0.5720 | | | |
| DIR | 0.5100 | 0.2710 | 0.2750 | 0.6080 | | |
| RDC | 0.5680 | 0.3160 | 0.2740 | 0.5270 | 0.4190 | |

and suitable for further structural analysis.

### *4.4 Structural Model Evaluation*

The structural model was evaluated after confirming that the measurement model met reliability and validity standards. As shown in Figure 3, the structural model specifies direct relationships among variables: Economic Policy Stability (EPS), Digital Infrastructure Readiness (DIR), Research and Development Capability (RDC), Artificial Intelligence Talent Capability (AITC), Digital Governance Capability (DGC), and Artificial Intelligence Innovation Performance (AIIP). The figure shows that all proposed paths are positive, indicating that factors such as policy stability, digital infrastructure, R&D, AI talent, and digital governance enhance AI innovation performance. Additionally, DGC serves as a mediator linking the four independent variables to AIIP. Thus, Figure 3 summarizes the estimated structural relationships before detailed assessments of collinearity, explanatory power, effect size, predictive relevance, and overall model fit.

The evaluation of the structural model assessed whether the proposed relationships among the latent variables were statistically valid before hypothesis testing. It analyzed collinearity, the coefficient of determination, effect sizes, predictive relevance, and model fit indices. The results indicate the model is appropriate for further analysis, with all inner VIF values below the recommended threshold, moderate explanatory power of the endogenous constructs, significant effect sizes from predictors, positive predictive relevance values, and acceptable overall model fit. Detailed outcomes are presented in Tables 10–14.

**Table 10.** **Collinearity Assessment**

| Structural Path | VIF |
|---|---|
| AITC > AIIP | 1.2060 |
| AITC > DGC | 1.1400 |
| EPS > AIIP | 1.3520 |
| EPS > DGC | 1.1250 |
| DGC > AIIP | 2.1090 |
| DIR > AIIP | 1.4530 |
| DIR > DGC | 1.2080 |
| RDC > AIIP | 1.3290 |
| RDC > DGC | 1.2270 |

Table 10 indicates that all inner VIF values range from 1.1250 to 2.1090, remaining below both the common threshold of 5.0000 and the more stringent threshold of 3.3000. The highest VIF was for the path DGC > AIIP at 2.1090, and the lowest was for EPS > DGC at 1.1250. These results imply that multicollinearity is not a major issue in the structural model. As a result, each predictor independently helps explain the endogenous constructs, enabling clear interpretation of the path coefficients without concern for excessive overlap among the predictor variables.

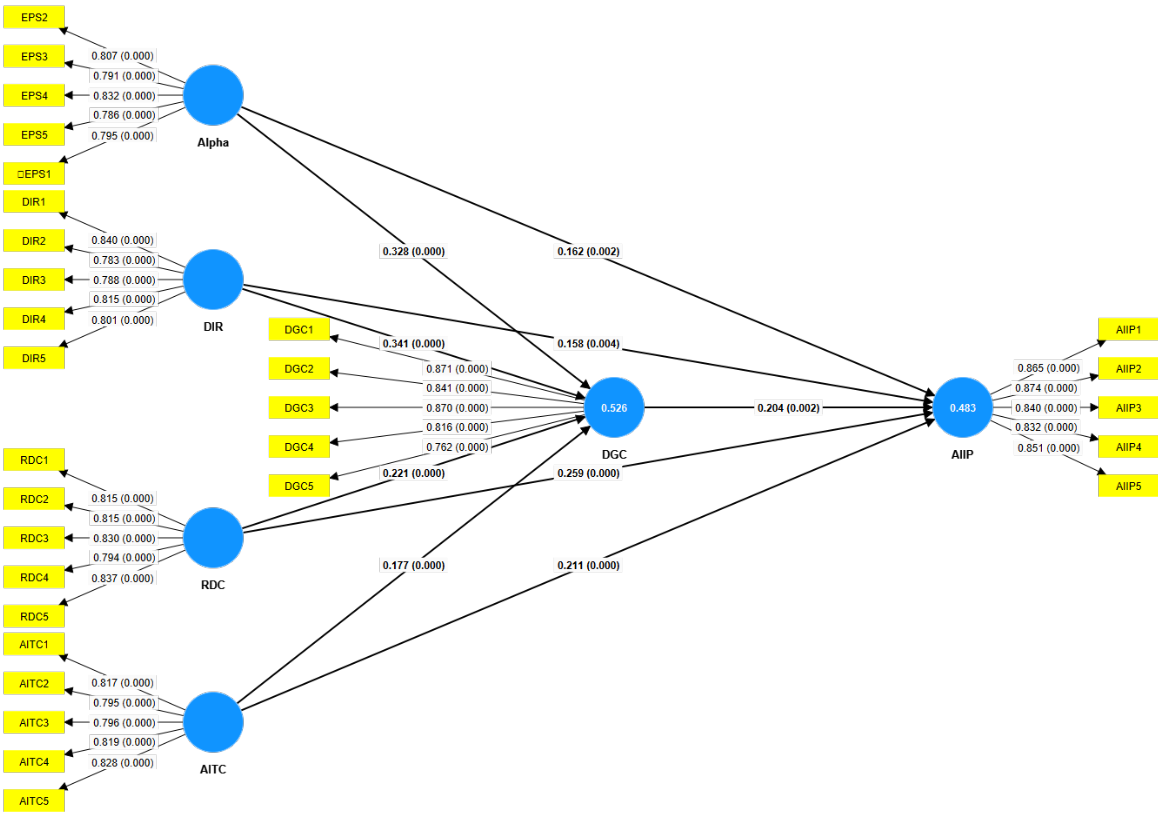


**Fig. 3.** Structural Model Results

**Table 11.** Coefficient of Determination

| Endogenous Construct | R-square | R-square Adjusted |
|---|---|---|
| AIIP | 0.4830 | 0.4720 |
| DGC | 0.5260 | 0.5180 |

Table 11 shows that the coefficient of determination reveals the model explains 48.3% of the variance in Artificial Intelligence Innovation Performance (AIIP) and 52.6000% in Digital Governance Capability (DGC). The adjusted R-squared values are 0.4720 for AIIP and 0.5180 for DGC, indicating the model's explanatory power remains stable after adjusting for predictors. These values suggest a moderate level of explanation. Specifically, EPS, DIR, RDC, AITC, and DGC together account for nearly half of the variation in AIIP, while EPS, DIR, RDC, and AITC collectively explain over half the variation in DGC.

As shown in Table 12, the effect size results demonstrate how much each exogenous construct influences the endogenous constructs. For AIIP, the most significant impact came from RDC > AIIP with an f-square of 0.0970, followed by AITC > AIIP at 0.0720, DGC > AIIP at 0.0380, EPS > AIIP at 0.0380, and DIR > AIIP at 0.0330. These indicate small yet meaningful effects on AIIP. Regarding DGC, the strongest effects were from DIR > DGC with an f-square of 0.2030 and EPS > DGC at 0.2020, both representing medium effects. Conversely, RDC > DGC had an f-square of 0.0840, and AITC > DGC was 0.0580, reflecting small effects.

Table 13 shows that the predictive relevance results yield positive Q-square values for the endogenous constructs. AIIP has a Q-square of 0.3440, and DGC has 0.3540. Since both are above zero, it indicates that the model has predictive relevance. This means the structural model not only accounts for variance but also has predictive capability. The positive scores

**Table 12.** Effect Size

| Structural Path | f-square | Interpretation |
|---|---|---|
| AITC > AIIP | 0.0720 | Small effect |
| AITC > DGC | 0.0580 | Small effect |
| EPS > AIIP | 0.0380 | Small effect |
| EPS > DGC | 0.2020 | Medium effect |
| DGC > AIIP | 0.0380 | Small effect |
| DIR > AIIP | 0.0330 | Small effect |
| DIR > DGC | 0.2030 | Medium effect |
| RDC > AIIP | 0.0970 | Small effect |
| RDC > DGC | 0.0840 | Small effect |

**Table 13.** Predictive Relevance

| Endogenous Construct | SSO | SSE | $Q^2$ |
|---|---|---|---|
| AIIP | 1250.0000 | 820.4140 | 0.3440 |
| DGC | 1250.0000 | 807.2970 | 0.3540 |

confirm that the model effectively forecasts digital governance capability and artificial intelligence innovation performance, demonstrating adequate relevance. Therefore, the model is suitable for explaining and predicting AI innovation outcomes in Indonesian manufacturing firms.

Table 14 shows that the fit indices for the proposed PLS-SEM model confirm its adequacy in representing the data. The SRMR value of 0.0480 is below the recommended threshold of 0.0800, indicating a good match between the observed and estimated correlation matrices. The NFI of 0.8670 suggests an acceptable fit for a complex predictive model. Furthermore, the d_ULS and d_G values are 1.0850 and 0.4070, respectively, with a chi-square value of 591.3360. Overall, these results affirm the model's suitability and support its use for hypothesis testing.

**Table 14.** **Model Fit Indices**

| Fit Index | Saturated | Estimated | Recommended Criterion | Interpretation |
|---|---|---|---|---|
| SRMR | 0.0480 | 0.0480 | < 0.080 | Good model fit |
| d_ULS | 1.0850 | 1.0850 | Lower values indicate a better fit | Acceptable |
| d_G | 0.4070 | 0.4070 | Lower values indicate a better fit | Acceptable |
| Chi-square | 591.3360 | 591.3360 | Reported as model fit information | Reported |
| NFI | 0.8670 | 0.8670 | Closer to 0.900 indicates a better fit | Acceptable |

**Table 15.** **Direct Effect Hypotheses Testing**

| Hypothesis | Structural Path | Original Sample | STDEV | T-statistics | P-value |
|---|---|---|---|---|---|
| H1 | EPS > AIIP | 0.1620 | 0.0530 | 3.0720 | 0.0020 |
| H2 | DIR > AIIP | 0.1580 | 0.0550 | 2.8880 | 0.0040 |
| H3 | RDC > AIIP | 0.2590 | 0.0540 | 4.8050 | 0.0000 |
| H4 | AITC > AIIP | 0.2110 | 0.0470 | 4.5120 | 0.0000 |
| H5 | EPS > DGC | 0.3280 | 0.0480 | 6.7750 | 0.0000 |
| H6 | DIR > DGC | 0.3410 | 0.0490 | 6.9990 | 0.0000 |
| H7 | RDC > DGC | 0.2210 | 0.0480 | 4.5600 | 0.0000 |
| H8 | AITC > DGC | 0.1770 | 0.0490 | 3.6400 | 0.0000 |
| H9 | DGC > AIIP | 0.2040 | 0.0670 | 3.0550 | 0.0020 |

### *4.5 Hypotheses Testing*

Hypothesis testing was conducted using the bootstrapping method in SmartPLS to assess the significance of both direct and indirect relationships among the constructs. Significance was determined based on t-statistics and p-values; relationships were considered significant if the t-statistic exceeded 1.9600 and the p-value was below 0.0500. As shown in Table 15, all direct effects were positive and statistically significant. The results revealed that Economic Policy Stability notably influenced Artificial Intelligence Innovation Performance ($\beta$ = 0.1620; t = 3.0720; p = 0.0020), supporting H1. Digital Infrastructure Readiness also positively impacted AIIP ($\beta$ = 0.1580; t = 2.8880; p = 0.0040), supporting H2. Furthermore, Research and Development Capability had the strongest direct effect on AIIP ($\beta$ = 0.2590; t = 4.8050; p = 0.0000), supporting H3, while Artificial Intelligence Talent Capability significantly enhanced AIIP ($\beta$ = 0.2110; t = 4.5120; p = 0.0000), supporting H4. Regarding the antecedents of Digital Governance Capability, the results show that Economic Policy Stability ($\beta$ = 0.3280; t = 6.7750; p = 0.0000), Digital Infrastructure Readiness ($\beta$ = 0.3410; t = 6.9990; p = 0.0000), Research and Development Capability ($\beta$ = 0.2210; t = 4.5600; p = 0.0000), and Artificial Intelligence Talent Capability ($\beta$ = 0.1770; t = 3.6400; p = 0.0000) all had significant positive effects on DGC, supporting H5, H6, H7, and H8. Finally, Digital Governance Capability significantly influenced AIIP ($\beta$ = 0.2040; t = 3.0550; p = 0.0020), supporting H9. These findings confirm that institutional stability, digital infrastructure, R&D capability, AI talent, and digital governance are key drivers of AI innovation performance.

As shown in Table 16, the analysis of indirect effects confirms that digital governance capability significantly mediates all examined relationships between the independent variables and artificial intelligence innovation performance (AIIP). The mediating role of DGC in the link between economic policy stability and AIIP was positive and statistically significant ($\beta$ = 0.0670; t = 2.7010; p = 0.0070), supporting H10. Likewise, the indirect effect of digital infrastructure readiness on AIIP via DGC was significant ($\beta$ = 0.0700; t = 2.7500; p = 0.0060), supporting H11. The findings further reveal that research and development capability significantly influences AIIP through DGC ($\beta$ = 0.0450; t = 2.5090; p = 0.0120), supporting H12. Additionally, Artificial Intelligence Talent Capability has a significant indirect effect on AIIP via DGC ($\beta$ = 0.0360; t = 2.4500; p = 0.0140), supporting H13. Since the direct effects in Table 15 remain significant and the indirect effects in Table 16 are also significant, this type of mediation is classified as partial mediation. This suggests that digital governance capability does not completely substitute for the direct effects of the independent variables on AIIP but enhances the mechanism through which policy stability, infrastructure readiness, R&D capacity, and AI talent capability translate into AI innovation performance.

### *4.6 Discussion*

The empirical evidence strongly supports the proposed framework, showing that factors like economic policy stability, digital infrastructure readiness, R&D capability, AI talent, and digital governance are key drivers of AI innovation performance. The results indicate that firms tend to achieve better AI-related innovations when operating in a stable policy environment with strong technological, knowledge, human, and governance capabilities. This aligns with the view that AI innovation is not just a technological feat but also a systemic ability influenced by institutional, organizational, and governance factors. The significant role of economic policy stability in AIIP supports real options theory, which suggests that stable policies lessen uncertainty and encourage firms to invest in irreversible innovations (Bernanke, 1983; Dixit and Pindyck, 1994). Prior studies also show that policy uncertainty can hinder corporate investment, R&D, and innovation outputs (Baker et al., 2016; Bhattacharya et al., 2017; Gulen and Ion, 2016; Tajaddini and Gholipour, 2021). Recent research on AI innovation confirms that economic policy uncertainty can notably limit innovation, particularly in countries with weaker innovation capacities.

The positive effects of digital infrastructure readiness, R&D capability, and AI talent capability on AIIP further confirm that AI innovation performance depends on the interplay among digital resources, knowledge generation, and specialized human skills. Digital infrastructure enables firms to manage large data volumes, deploy cloud systems, secure digital operations, and scale AI applications. This aligns with research highlighting

**Table 16.** **Indirect Effect and Mediation Testing**

| Hypothesis | Indirect Path | Original Sample | STDEV | T-statistics | P-value | Mediation Type | Decision |
|---|---|---|---|---|---|---|---|
| H10 | EPS > DGC > AIIP | 0.0670 | 0.0250 | 2.7010 | 0.0070 | Partial mediation | Supported |
| H11 | DIR > DGC > AIIP | 0.0700 | 0.0250 | 2.7500 | 0.0060 | Partial mediation | Supported |
| H12 | RDC > DGC > AIIP | 0.0450 | 0.0180 | 2.5090 | 0.0120 | Partial mediation | Supported |
| H13 | AITC > DGC > AIIP | 0.0360 | 0.0150 | 2.4500 | 0.0140 | Partial mediation | Supported |

the role of data infrastructure, computational power, and digital platforms in AI-led innovation (Igna and Venturini, 2023; Johnson et al., 2022; Mariani et al., 2023). The significant influence of R&D capability indicates that experimentation, knowledge development, collaboration, and commercialization are vital to AI innovation. This supports the absorptive capacity theory, which holds that firms with stronger knowledge capabilities are better equipped to recognize, integrate, and use external knowledge for innovation (Cohen and Levinthal, 1990). Likewise, the notable effect of AI Talent Capability reinforces the Resource-Based View, which suggests that valuable, difficult-to-copy human capital can serve as a continuous source of competitive advantage (Barney, 1991).

The findings also show that Digital Governance Capability has a notable direct effect on AIIP and mediates all four relationships between the independent variables and AIIP. This suggests that policy stability, infrastructure readiness, R&D capability, and AI talent alone are insufficient to achieve AI innovation performance unless firms effectively govern data, ensure ethical AI use, comply with regulations, maintain transparency, and manage digital risks. The partial mediation indicates that Digital Governance Capability enhances, rather than replaces, the influence of institutional and organizational capabilities on AIIP. This aligns with AI governance literature, which highlights that responsible AI practices, transparency, risk management, and regulatory compliance are vital for turning AI potential into organizational value (Kaplan and Haenlein, 2020; Morley et al., 2020; OECD, 2024).

Overall, this research broadens the AI innovation literature by demonstrating that AI innovation performance in Indonesian manufacturing companies depends on both external policy stability and internal organizational skills. The results align with Dynamic Capabilities Theory, showing that firms must continually develop, integrate, and reconfigure digital infrastructure, R&D processes, AI talent, and governance structures to keep pace with AI-driven changes (Teece et al., 1997). Practically, manufacturers should see AI adoption not only as a technical upgrade but as a key part of their overall strategy. They need to monitor policies, ensure infrastructure readiness, invest in R&D, develop AI expertise, and implement digital governance to build a more resilient AI innovation ecosystem.

## 5. Conclusion

This study explored how factors such as Economic Policy Stability, Digital Infrastructure Readiness, Research and Development Capability, and Artificial Intelligence Talent Capability influence AI Innovation Performance, with Digital Governance Capability acting as a mediating factor. The results demonstrate that all direct relationships are positive and statistically significant. Specifically, economic policy stability, digital infrastructure, R&D capacity, and AI talent directly enhance AI Innovation Performance. These findings suggest that AI innovation in Indonesian manufacturing companies depends on a combination of policy stability, infrastructure, research, and human resources, rather than any single factor. Additionally, Digital Governance Capability also positively and significantly impacts AI Innovation Performance, highlighting the importance of data governance, ethical AI practices, compliance, transparency, and risk management in transforming AI resources into innovative outcomes.

The mediation analysis indicates that Digital Governance Capability partially mediates the link between each of the four independent variables and artificial intelligence innovation performance. This suggests that factors such as stable economic policies, robust digital infrastructure, R&D capabilities, and AI talent can enhance AI innovation both directly and by strengthening digital governance. The findings imply that Indonesian manufacturing firms should view AI adoption as more than merely a technological upgrade. Effective AI innovation depends on an integrated ecosystem where institutional stability, organizational skills, digital infrastructure, human resources, and governance systems collaborate. Overall, the study confirms that digital governance capability is vital for building a resilient innovation ecosystem and for advancing AI-driven products, processes, services, business models, and competitiveness.

### *Theoretical Implications*

This study broadens the existing literature by integrating Real Options Theory, Dynamic Capabilities Theory, the National Innovation System Theory, and the Resource-Based View into a unified framework for understanding Artificial Intelligence Innovation Performance. The significant influence of Economic Policy Stability supports the principles of Real Options Theory, demonstrating that stable policies reduce uncertainty and encourage firms to invest in AI innovation. The important roles of Digital Infrastructure Readiness, R&D Capability, and AI Talent Capability correspond with Dynamic Capabilities Theory and the Resource-Based View, highlighting that firms need to develop and adapt technological, knowledge-based, and human resources to succeed in AI innovation. Moreover, the mediating role of Digital Governance Capability advances current AI innovation research by showing that governance functions not only as a control mechanism but also as a strategic resource linking institutional and organizational factors to innovation success.

### *Practical Implications*

The results indicate several actionable recommendations for manufacturing firms. Managers are encouraged to enhance AI innovation by investing in both AI technologies and the organizational skills necessary to deploy them effectively. Companies should bolster their digital infrastructure, create integrated data systems, boost R&D initiatives, and upgrade AI-related competencies among staff through continuous training and cross-departmental collaboration. The study also emphasizes the importance of Digital Governance Capability.

Organizations should establish clear data governance policies, uphold ethical AI standards, implement compliance procedures, ensure transparent digital decision-making, and adopt systematic AI risk management strategies. Implementing these measures can mitigate risks during deployment, foster stakeholder confidence, and convert AI adoption into concrete innovation results.

### *Policy Implications*

The findings also have significant implications for policymakers. Consistent economic policies are essential to promote AI innovation, with predictable regulations, clear digital frameworks, stable taxation, and coordinated government efforts being key to attracting AI investment. Policymakers should create a stable and supportive regulatory environment that reduces uncertainty for companies adopting AI. Furthermore, public policies ought to support the development of digital infrastructure, encourage the growth of AI talent, provide incentives for R&D, and ensure responsible AI governance. For emerging economies like Indonesia, strengthening the national AI innovation ecosystem requires effective coordination among government bodies, industry players, universities, and tech providers.

### *Research Limitations*

This study has several limitations. First, it focuses on Indonesian manufacturing firms, which may limit how broadly the findings apply to other sectors or countries. Second, relying on survey data means capturing respondents' perceptions, subject to potential bias. Third, using a cross-sectional design examines relationships at a single point in time, limiting insights into long-term shifts in AI adoption and innovation outcomes. Fourth, while Digital Governance Capability is explored as a mediator, other mechanisms, such as organizational learning, absorptive capacity, digital culture, and strategic agility, are not considered in the model.

### *Future Research Directions*

Future studies could broaden this research by examining additional sectors such as financial services, healthcare, logistics, energy, and technology-driven service firms. Cross-country comparisons might also provide deeper insights into how policy stability and digital governance influence AI innovation across different institutional settings. Long-term data could be used to observe how AI innovation performance evolves as companies enhance their digital infrastructure, R&D capabilities, AI talent, and governance frameworks. Additionally, future research could explore other mediating or moderating factors like absorptive capacity, digital transformation strategies, organizational agility, innovation culture, or environmental uncertainty. Qualitative or mixed-methods approaches can help clarify how firms develop and implement digital governance practices within actual AI innovation projects.

## Declarations

### CRediT authorship contribution statement

**Ahmad Rizani:** Conceptualization, Methodology, Investigation, Data curation, Formal analysis, Software, Writing—original draft, Writing—review & editing.
**Tri Darsono:** Supervision, Validation, Methodological refinement, Theoretical framework development, Writing—review & editing.
**Gehad Mohammed Sultan Saif:** Literature review, Data interpretation, Visualization, Critical revision, Writing—review & editing.

### Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have influenced the work reported in this paper. The authors also confirm that there are no professional, institutional, or personal relationships that may be perceived as affecting the objectivity, integrity, or interpretation of the research findings.


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### Data availability statement

The data that support the findings of this study are available from the corresponding author upon reasonable request. The data are not publicly available due to confidentiality concerns regarding respondent information and institutional data-use policies. Any request for data access will be considered in accordance with academic research ethics, respondent confidentiality, and the purpose of data use.

### Ethics statement

This study used voluntary survey data from respondents in Indonesian manufacturing firms. Participants were informed that responses would be used only for academic purposes. No sensitive personal information was collected, and all data were processed anonymously and confidentially, in accordance with academic integrity, responsible data handling, and objective analysis principles.

### Informed consent statement

Informed consent was obtained from all respondents before they participated in the survey. Respondents were informed of the study's general purpose, the voluntary nature of participation, the confidentiality of their responses, and the use of the collected data for academic analysis and publication only.

### Use of generative AI and AI-assisted technologies

During the preparation of this manuscript, the authors may have used AI-assisted tools to support language refinement, grammar checking, consistency in formatting, and improvements in readability. All intellectual content, conceptual development, data interpretation, analysis, and final conclusions were reviewed, verified, and approved by the authors. The authors take full responsibility for the accuracy, integrity, and originality of the final manuscript.


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