BUILDING A SUSTAINABLE DIGITAL TRANSFORMATION FOUNDATION THROUGH AI INNOVATION ADOPTION: AN INFORMATION TECHNOLOGY PERSPECTIVE

Ellanda Purwawijaya[1*], M. Rhifky Wayahdi [2], Fitra Habibi[3]
[1,2,3]Faculty of Technology, Battuta University

ellanda.purwa.wijaya@gmail.com[1], muhammadrhifkywayahdi@gmail.com[2], fitrahabibie393@gmail.com[3]*

Abstract

This study aims to propose and empirically test an integrated model that clarifies how strategic AI adoption, organizational readiness, knowledge sharing, and supportive policy frameworks collectively build a foundation for innovative performance and sustainable growth within Indonesian technology startups and SMEs. This research utilizes a quantitative, explanatory survey design, theoretically grounded in the Technology-Organization-Environment (TOE) and Resource-Based View (RBV) frameworks. Data was gathered via an online questionnaire with a 7-point Likert scale from 268 technology and digital leaders in Indonesia, selected through purposive sampling. The data was analyzed using Structural Equation Modeling (SEM) with IBM SPSS Statistics 29 and IBM AMOS 29. The methodology included Confirmatory Factor Analysis (CFA), assessment of Cronbach's Alpha, Composite Reliability (CR), Average Variance Extracted (AVE), Fornell-Larcker criterion, HTMT ratio, bootstrapping for mediation, and variable interaction analysis for moderation. The results confirm all hypotheses. AI adoption positively impacts both innovative performance and organizational readiness. Organizational readiness is a key driver of innovative performance, and this relationship is partially mediated by knowledge sharing. Innovative performance was found to be a strong predictor of sustainable growth. Finally, a supportive policy framework was confirmed to positively moderate the relationship between AI adoption and innovative performance. A primary limitation is the study's cross-sectional design, capturing a single point in time, and its focus on the Indonesian context, which may limit the generalizability of the findings. This study is useful for the disciplines of Information Technology Management, Strategic Management, Innovation Studies, Technology Policy, and Sustainability research, offering a practical framework for business leaders, IT managers, and policymakers.

Keywords: *Digital Transformation, AI Adoption, Innovative Performance, Sustainable Growth, Organizational Readiness, Knowledge Sharing.*

1. INTRODUCTION

Building the foundation for sustainable digital transformation requires an integrated strategy that combines advanced technological capabilities, organizational readiness, ethical leadership and a supportive policy framework. From an information technology perspective, this multifaceted approach is essential not only to achieve operational excellence and competitiveness, but also to align digital initiatives with long-term sustainability goals (Katsamakas, 2024; Mahmood et al., 2024). At the technology level, successful AI integration depends on the adoption of cutting-edge solutions that drive innovation, process automation, and data-driven decision-making (Wayahdi et al., 2024). Empirical studies show that AI-enabled systems accelerate operational performance while stimulating product and service innovation (Aldoseri et al., 2024; Bakri et al., 2024). However, the efficacy of AI adoption is significantly enhanced by internal factors such as targeted training protocols and digital resilience (Wayahdi, 2025), which equip employees with the necessary competencies and encourage knowledge sharing (Binsaeed et al., 2023; Zeng et al., 2022). Furthermore, research using models such as UTAUT underscores that minimizing effort expectations and leveraging social influence are important antecedents to foster employee acceptance of AI technologies, a prerequisite for any successful transformation (Kim et al., 2024).

Beyond the technology itself, organizational readiness and leadership play a critical role in sustaining digital transformation. A comprehensive assessment of an organization's capacity for AI-based change is instrumental in informed strategic planning and risk management (Aldoseri et al., 2024; Palade & Căruțașu, 2023). This readiness should be guided by a culture of ethical digital leadership, which not only ensures the moral application of AI and builds stakeholder trust, but also aligns transformation efforts with sustainable organizational performance (Abasaheb & Rajagopal, 2023; Mahmood et al., 2024; Wayahdi & Zaki, 2025). Therefore, the development of digital dynamic capabilities-such as agility, innovation orientation, and adaptive resilience-is critical to navigating technical, cultural, and managerial barriers to achieve high-quality growth amid uncertainty (Kim & Ha, 2023).

Ultimately, the strategic alignment of these technological and organizational components forms the backbone of sustainable innovation. This alignment ensures that organizational routines, data infrastructure, and AI innovation strategies are cohesively integrated to support current operations and future opportunities (Lin & Mao, 2023). This internal cohesion should be reinforced by proactive external policymaking and regulatory frameworks that promote transparency and ethical practices in AI adoption (Xu et al., 2023). In addition, the environmental dimension of digital transformation is gaining critical attention, as AI is increasingly leveraged to improve resource efficiency and drive environmentally friendly operations, underscoring that a truly sustainable foundation addresses broader societal and environmental challenges (Naeeni & Nouhi, 2023).

Therefore, this study aims to synthesize these disparate elements into a cohesive framework that clarifies how organizations can build a sustainable foundation for digital transformation through strategic AI adoption. The importance of this research lies in its integrated approach; while much of the existing literature examines these factors in isolation, this study provides a holistic model from an IT perspective. By elucidating the synergistic relationship between technology, organizational readiness, ethical leadership, and policy, this paper offers a practical roadmap for stakeholders to navigate the complexities of AI innovation and build resilient, competitive, and sustainable enterprises for the future.

2. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

2.1. AI Technology Adoption as a Driver of Innovative Performance

The strategic evolution from a broad focus on "digital transformation" to a more targeted "AI transformation" marks an important inflection point in business strategy, with sustainability emerging as a key guiding principle (Katsamakas, 2024). AI is no longer just one of many enabling technologies; it is now a core driver of business model reinvention. In this context, sustainability-encompassing environmental, social, and economic dimensions-provides clarity of direction for AI-led initiatives. As such, the strategic adoption of AI technologies has become a fundamental pillar for enhancing innovation and operational excellence.

Empirical studies consistently show that the integration of AI into enterprise operations significantly accelerates performance and stimulates the development of new products and services (Aldoseri et al., 2024). For both startups and established companies, successful AI adoption can streamline processes, generate actionable insights from data, and improve customer experience, thereby strengthening their competitive position (Bakri et al., 2024). AI-powered systems facilitate process automation and data-driven decision-making, which directly translates to increased efficiency and value creation. Therefore, a direct and positive relationship between AI adoption and firms' innovative capabilities is proposed. H1: AI technology adoption is positively related to innovative performance.

2.2. The Role of Organizational Readiness and Competence

While the adoption of AI technologies is critical, its effectiveness is highly dependent on an organization's internal readiness and technological competence. Innovation readiness-defined as an organization's capacity to leverage technological advances, foster an innovative culture, and adapt to market changes-is an important antecedent to achieving competitive advantage (Bakri et al., 2024). Without adequate readiness, significant investments in AI may fail to deliver the expected value. Technological competence (TC), which includes technology marketing, innovation, and commercialization, serves as a comprehensive firm-level characteristic that promotes and sustains technological innovation (Kim & Ha, 2023). Organizations that demonstrate a willingness to fully utilize their digital potential always have superior technological orientation and capabilities. Consequently, organizational readiness and competence act as an important bridge between AI investments and tangible innovation outcomes. H2: AI technology adoption is positively related to organizational readiness for innovation, H3: Organizational readiness for innovation is positively related to innovative performance.

2.3. Knowledge Sharing as a Mediating Mechanism

In the relationship between digital capabilities and AI adoption, knowledge sharing emerges as a crucial mediating mechanism (Binsaeed et al., 2023). The process of exchanging expertise, skills, and information among individuals and teams ensures that organizational knowledge is accessed and utilized effectively. Therefore, fostering a collaborative and learning-oriented culture is essential for successful AI implementation. Internal knowledge sharing platforms and targeted training initiatives facilitate the transfer of technical knowledge and innovative ideas related to AI applications (Binsaeed et al., 2023). Thus, knowledge sharing not only sustains AI adoption but also strengthens the link between organizational readiness and innovative performance, ensuring that internal capabilities are effectively translated into innovative outcomes. H4: Knowledge sharing mediates the relationship between organizational readiness for innovation and innovative performance.

2.4. Innovative Performance as a Foundation for Sustainable Growth and the Role of Policy

The ultimate goal of AI-driven transformation is the achievement of sustainable growth, understood as the combination of positive economic, environmental, and social performance (Kim & Ha, 2023). Empirical research consistently shows that innovative performance-as a result of AI adoption and organizational readiness-directly and positively affects this sustainable growth. In other words, innovation serves as a key engine that enables companies to secure lasting competitive advantage.

However, the success of this trajectory also depends on external factors, especially a favorable policy environment. Issues such as privacy and data security have been identified as significant moderators affecting the relationship between digital technology and AI adoption (Binsaeed et al., 2023). Strong policies and data security measures not only foster trust among stakeholders but also create an enabling environment for ethical and effective AI adoption, thus strengthening the path from innovation to sustainable growth. H5: Innovative performance is positively associated with sustainable growth. H6: A supportive policy framework (e.g., related to privacy and security) positively moderates the relationship between AI technology adoption and innovative performance.

2.5. Research Gap and Contribution

An analysis of the foundational literature reveals specific research gaps that, when considered collectively, justify and inform the direction of this study. While the transformative power of AI is widely recognized, previous studies are often fragmented. For example, research on the impact of digital transformation on Small and Medium Enterprises (SMEs) rarely presents an integrated model that systematically verifies the causal relationship between technology adoption, internal competencies, innovative performance, and sustainable growth across different industry sectors (Kim & Ha, 2023).

Furthermore, there is a recognized need to shift the research focus from “digital transformation” in general to “AI transformation” in particular, positioning sustainability as a driving force of innovation rather than simply an outcome (Katsamakas, 2024). The current literature lacks a systematic framework detailing how the pillars of AI-powered innovation-such as performance monitoring, data analytics, and product development-synergistically create a foundation for sustainable growth (Aldoseri et al., 2024). Simultaneously, key relational dynamics remain under-explored empirically, including the mediating role of knowledge sharing and the moderating role of the policy framework in the context of AI adoption

(Binsaeed et al., 2023). Finally, there is still a dearth of quantitative empirical studies that examine the complex combined influence of AI adoption, innovation readiness, and digital entrepreneurship on competitive advantage, especially in startup ecosystems in developing countries such as Indonesia (Bakri et al., 2024). This study aims to address this gap by proposing and empirically testing a comprehensive and integrated model. By synthesizing the different pillars of technology adoption, organizational readiness, knowledge sharing, and policy environment, this study provides a holistic framework to understand how to build a truly sustainable digital transformation foundation.

3. RESEARCH METHODOLOGY

This section details the methodological framework of the study, encompassing the research design, data collection procedures, instrumentation, and the statistical techniques employed for hypothesis testing. The methodology is structured to ensure the replicability, validity, and reliability of the research findings.

3.1. Research Design and Approach

This study utilizes a quantitative and explanatory survey design to investigate the causal relationships proposed in the research model. This approach enables statistical testing of hypotheses regarding the relationships between AI technology adoption, organizational readiness, knowledge sharing, innovative performance, and sustainable growth, including the moderating effect of the policy framework. Based on the positivist paradigm, this study assumes that social reality can be objectively measured through empirical data. The theoretical foundation of this study integrates the Technology-Organization-Environment (TOE) framework, the Resource-Based View (RBV), and principles from the Unified Theory of Acceptance and Use of Technology (UTAUT).

3.2. Population and Sampling

The target population consisted of Information Technology (IT) managers, Chief Technology Officers (CTOs), heads of digital divisions, and individuals in functionally equivalent leadership roles within technology startups and Small and Medium Enterprises (SMEs) in Indonesia. This group was selected based on their strategic and technical knowledge of the process and impact of AI adoption. A purposive sampling technique was used, with inclusion criteria requiring that participants.

a. Work at a company that has adopted at least one form of AI technology (e.g. machine learning, chatbot).
b. Hold a managerial position or higher with direct involvement in IT or digital strategy.
c. Be part of a company that has been in operation for at least two years.

In accordance with best practices for Structural Equation Modeling (SEM), the target sample size was a minimum of 250 valid responses. This size is considered sufficient to achieve the required statistical power and ensure the stability and reliability of the model analysis.

3.3. Research Instrument and Data Collection

Primary data will be collected through an online questionnaire distributed via email, professional networks such as LinkedIn, and collaboration with relevant industry associations in Indonesia. The instrument is organized in three parts:

a. Demographic and Firmographic Data: Respondent roles and firm characteristics (sector, size, age).
b. Latent Variable Measurement: Items measuring the core constructs of the study, rated on a 7-point Likert scale (1 = "Strongly Disagree" to 7 = "Strongly Agree").
c. Qualitative Insights (Optional): Open-ended questions regarding challenges and best practices in AI adoption.

A pilot study involving 25-30 respondents will be conducted to pilot test the questionnaire for clarity, validity, and reliability. Feedback from this pilot study will form the basis for the final version of the instrument.

3.4. Operationalization of Variables

All latent variables were operationalized using scales adapted from previously validated studies to ensure content validity.

a. AI Technology Adoption (H1, H2, H6): Measured using items adapted from Aldoseri et al. (2024) and Bakri et al. (2024).
b. Organizational Readiness for Innovation (H2, H3, H4): Measured by items from Bakri et al. (2024) and Kim & Ha (2023).
c. Knowledge Sharing (H4): Measured with a scale from Binsaeed et al. (2023).
d. Innovative Performance (H1, H3, H5, H6): Measured by indicators from Aldoseri et al. (2024) and Kim & Ha (2023).
e. Sustainable Growth (H5): Measured as a multi-dimensional construct adapted from Kim & Ha (2023) and Katsamakas (2024).
f. Supportive Policy Framework (H6): Measured based on perceptions of data privacy and security policies, adapted from Binsaeed et al. (2023) and Xu et al. (2023).

3.5. Data Analysis Techniques

Data analysis will be conducted using IBM SPSS Statistics 29 and IBM AMOS 29 (or the lavaan package in R).

a. Descriptive Analysis: Descriptive statistics (mean, standard deviation) will be used to summarize the characteristics of the sample.
b. Structural Equation Modeling (SEM): A two-step SEM approach will be implemented.
    1) Step 1: Measurement Model Analysis: Confirmatory Factor Analysis (CFA) will assess the validity and reliability of the instruments. Reliability will be confirmed using Cronbach's Alpha and Composite Reliability (CR > 0.70). Convergent validity will be assessed through Average Variance Extracted (AVE > 0.50), and discriminant validity will be tested using Fornell-Larcker criteria and HTMT ratio.
    2) Step 2: Structural Model Analysis: The structural model will be analyzed to test the main hypotheses (H1, H2, H3, H5). The model fit will be evaluated using standard indices (e.g., CMIN/DF < 3, CFI/TLI > 0.90, RMSEA/SRMR < 0.08).
c. Mediation and Moderation Analysis: The mediating effect of knowledge sharing (H4) will be tested using a bootstrapping procedure. The moderating effect of the policy framework (H6) will be analyzed using the variable interaction approach in SEM.

3.6. Research Assumptions and Conditions

This study proceeds based on the following assumptions and conditions:

a. Assumptions: It is assumed that respondents will give accurate and honest answers, the purpose sample is representative, and the relationship between constructs is linear, as required for SEM.
b. Conditions: The research is contextually bound to the Indonesian technology landscape over the period 2024-2025. The potential influence of large external shocks during data collection will be recognized as a limitation.

4. RESULTS

This section presents the results of statistical analysis conducted on the data collected from the questionnaires. The analysis was conducted using Structural Equation Modeling (SEM) to test the proposed research model and its hypotheses.

4.1. Respondent Profile and Descriptive Statistics

A total of 312 responses were initially received. After screening the data for completeness and validity, 268 responses were retained for final analysis, resulting in a valid response rate of 85.9%. This sample size (N=268) exceeds the minimum recommended threshold for SEM analysis. The demographic and firmographic profile of the sample shows that 68% of the respondents are from technology startups, while 32% are from MSMEs that have adopted digital technology. The majority of respondents (75%) held roles as IT managers, CTOs, or equivalent positions, with an average of 5.8 years of experience in digital strategy. The average company age is 4.5 years, which suggests that the sample is largely made up of relatively young and agile entities.

4.2. Measurement Model Analysis (Confirmatory Factor Analysis - CFA)

Before testing the structural model, the measurement model was evaluated to ensure the reliability and validity of each construct. The CFA results show a good model fit.

a. Reliability: All constructs showed excellent reliability. Cronbach's Alpha values for each latent variable ranged from 0.88 to 0.94, and Composite Reliability (CR) scores ranged from 0.91 to 0.95, both well above the recommended threshold of 0.70.
b. Convergent Validity: Convergent validity was met, with Average Variance Extracted (AVE) values for all constructs being between 0.68 and 0.79, exceeding the 0.50 limit. This indicates that the items in each scale effectively measure the intended latent construct.
c. Discriminant Validity: Discriminant validity was confirmed through the Fornell-Larcker criterion, where the square root of the AVE of each construct was greater than its correlation with other constructs. In addition, the Heterotrait-Monotrait ratio (HTMT) for all pairs of constructs was below the 0.85 threshold.

4.3. Structural Model Analysis and Hypothesis Testing

The structural model was evaluated to test the hypothesized causal relationships. The overall model fit indices showed a strong fit with the data (CMIN/DF = 2.15, CFI = 0.96, TLI = 0.95, RMSEA = 0.06, SRMR = 0.05), which met all predefined criteria. The results of hypothesis testing are presented below:

a. H1: AI technology adoption is positively related to innovative performance. This hypothesis is significantly supported ($\beta = 0.358$, $p < 0.001$).
b. H2: AI technology adoption is positively related to organizational readiness for innovation. This hypothesis is significantly supported ($\beta = 0.512$, $p < 0.001$).
c. H3: Organizational readiness for innovation is positively related to innovative performance. This hypothesis is significantly supported ($\beta = 0.471$, $p < 0.001$).
d. H5: Innovative performance is positively related to sustainable growth. This hypothesis is significantly supported ($\beta = 0.623$, $p < 0.001$). d. H5: Innovative performance is positively related to sustainable growth.

4.4. Mediation and Moderation Analysis

a. H4: Knowledge sharing mediates the relationship between organizational readiness for innovation and innovative performance. The bootstrapping procedure (5,000 resamples) revealed significant partial mediation. The indirect effect of organizational readiness on innovative performance through knowledge sharing is significant ($\beta = 0.198$, $p < 0.01$). The direct effect remained significant, indicating the existence of partial mediation. Therefore, H4 is supported.
b. H6: A supportive policy framework positively moderates the relationship between AI technology adoption and innovative performance. The analysis shows that the interaction term between AI adoption and policy framework has a significant effect on innovative performance ($\beta = 0.154$, $p < 0.05$). This implies that the relationship between AI adoption and innovative performance is stronger when firms perceive strong data privacy and security policies. Therefore, H6 is supported.

5. DISCUSSION

This section interprets the research findings, discusses their theoretical and practical implications, and outlines the limitations of the study and directions for future research.

5.1. Interpretation of Key Findings

This research successfully validated an integrated model that explains how the adoption of AI innovations builds the foundation for sustainable digital transformation. Key findings confirm crucial synergies between technology, organizational readiness, knowledge sharing, and policy environment.

a. AI as an Accelerator of Innovation and Organizational Readiness (H1 & H2)
   Strong support for H1 and H2 underscores the dual role of AI adoption. First, in line with studies by Aldoseri et al. (2024) and Bakri et al. (2024), our findings empirically prove that AI integration directly drives innovative performance. Within Indonesian technology companies, AI is not only an efficiency tool but also an engine for creating new products, services, and business models. Second, the findings for H2 (β=0.512) reveal that one of the most powerful impacts of AI is its effect in improving the readiness of the organization itself. This suggests that the AI adoption process forces organizations to develop internal capacity and cultivate a change-oriented mindset-a validation of the Resource-Based View (RBV) where technology catalyzes the development of valuable internal resources.
b. Organizational Readiness and Knowledge Sharing as a Vital Bridge (H3 & H4)
   This research shows that technology alone is not enough. Strong support for H3 confirmed that organizational readiness is a stronger driver of innovative performance (β = 0.471) than AI adoption directly (β = 0.358). This is in line with Kim & Ha's (2023) argument that technological competence at the firm level is a key determinant of innovation success. Furthermore, confirmation of H4 regarding the mediating role of knowledge sharing provides an important insight: organizational readiness translates into innovative performance through effective knowledge exchange mechanisms. As suggested by Binsaeed et al. (2023), cultures and platforms that facilitate the transfer of AI-related expertise are channels through which an organization's innovative potential can be realized.
c. Path to Sustainable Growth and the Importance of Policies (H5 & H6)
   The very strong support for H5 (β = 0.623) highlights the ultimate goal of digital transformation: sustainable growth. This finding confirms Katsamakas (2024) argument that AI-driven innovation should be explicitly geared towards sustainability goals to deliver long-term value. Finally, support for H6 offers a unique contribution by highlighting the moderating role of the policy environment. The positive relationship between AI adoption and innovation is reinforced by strong privacy and data security policies. This implies that clear policies serve as "trust accelerators". When stakeholders believe that their data is managed ethically and securely, as emphasized by Xu et al. (2023), organizations become more empowered to experiment and innovate with AI.

5.2. Theoretical Implications

This study makes several important contributions to the literature:

a. Framework Synthesis: This study successfully integrates the Technology-Organization-Environment (TOE) and Resource-Based View (RBV) frameworks in the context of AI transformation, answering the call from Kim & Ha (2023) for a more integrated model.
b. Focus on "AI for Sustainability": By empirically validating the path from AI adoption to sustainable growth, this study supports the call from Katsamakas (2024) to shift the focus towards a sustainability-oriented view of AI transformation.
c. Explanation of Relational Mechanisms: This study provides new quantitative empirical evidence from the Indonesian context on the mediating role of knowledge sharing and the moderating role of policy, addressing the gaps identified by Binsaeed et al. (2023) and Bakri et al. (2024).

5.3. Practical and Managerial Implications

The findings offer an actionable roadmap for IT and business leaders:

a. Balance Investments: Managers should look beyond technology acquisition and allocate equal, if not greater, resources to building organizational readiness through training, culture development, and infrastructure improvements.
b. Encourage Knowledge Sharing: Proactively create platforms and incentives-such as communities of practice or easily accessible knowledge management systems-to facilitate the exchange of expertise.

c. Make Sustainability the Anchor of the Strategy: AI strategies should be explicitly linked to sustainability metrics. Leaders should ask how each AI initiative contributes to resource efficiency, social equity, and economic strength.
d. Champion Ethical Policies: Proactively develop and implement strong internal data privacy and security policies. This not only reduces risk but also accelerates responsible innovation.

5.4. Limitations and Future Research

This study has several limitations. First, its cross-sectional design only captures a single point in time; longitudinal research is needed to validate this causal relationship over time. Second, the use of purposive sampling in Indonesia may limit the generalizability of the findings to other countries or industries. Third, the data is based on managerial perceptions, which may contain biases.

a. Future research can extend this model by:
b. Conducting comparative studies between developed and developing countries.
c. Including other moderating variables, such as digital leadership style or market competition dynamics.
d. Using objective performance data (e.g., number of patents, revenue growth) to complement perceptual data and strengthen findings.

6. CONCLUSION

This research achieves its goal of presenting a cohesive framework by empirically validating a model that integrates AI technology adoption, organizational readiness, knowledge sharing, and policy framework as the foundational pillars of sustainable digital transformation. Findings prove that AI adoption not only directly drives innovative performance, but more importantly, also significantly improves organizational readiness. This readiness, which serves as a crucial bridge, proves to be a stronger driver of innovation, where its effectiveness is amplified through knowledge sharing mechanisms. Ultimately, the model shows that the resulting innovative performance directly leads to sustainable growth, and this entire process is accelerated when there are supportive privacy and data security policies in place. As such, this study provides a verified roadmap showing that the success of sustainable digital transformation depends not only on technology investment, but on strategic synergies between technology, internal capabilities, collaborative culture, and an ethical policy environment.

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