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# Innovation Strategies, Intellectual Capital, and Competitive Advantage in Indonesian Manufacturing Firms

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**Abstract**

**Objective –** This study aims to examine the effects of green product innovation, R&D investment, and AI adoption on competitive advantage in Indonesian manufacturing firms. It also investigates whether intellectual capital and government support strengthen these relationships.

**Design/methodology/approach –** A quantitative research design was employed using Partial Least Squares Structural Equation Modeling (PLS-SEM). Data were collected from manufacturing firms in Indonesia to test the direct effects of green product innovation, R&D investment, and AI adoption on competitive advantage, as well as the moderating roles of intellectual capital and government support.

**Findings –** The findings show that green product innovation, R&D investment, and AI adoption significantly improve competitive advantage, with green innovation having the strongest effect. Intellectual capital only strengthens the green innovation–competitive advantage relationship, while government support strengthens green innovation and R&D effects. However, neither moderator significantly enhances AI adoption's impact, indicating that innovation-led competitiveness depends on the specific strategy and supporting resources.

**Research limitations/implications –** This study is limited to manufacturing firms in Indonesia, which may constrain the generalisability of the findings. The study contributes to the strategic management literature by offering an integrated framework that links innovation strategies, intellectual capital, and government support to competitive advantage.

**Practical implications –** Managers should develop integrated innovation strategies supported by intellectual capital, while policymakers should provide targeted incentives and technical support to facilitate innovation adoption.

**Originality/value –** This study provides a comprehensive understanding of how internal resources and external support interact to drive innovation-led competitiveness in an emerging market context.

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## INTRODUCTION

The global manufacturing industry is in the midst of a transformative phase, influenced by growing sustainability demands, technological advancements, and escalating competition. The transition to more sustainable practices, driven by both market forces and regulatory requirements, requires firms to rethink their innovation strategies. Green product innovation, research and development (R&D) investments, and the adoption of artificial intelligence (AI) are becoming increasingly recognized as critical drivers for enhancing competitive advantage. These strategies not only contribute to the sustainable management of resources but also provide firms with opportunities to maintain competitive advantages in dynamic markets (Hart, 1995). However, the degree to which these strategies lead to competitive advantage depends significantly on how effectively firms develop and integrate their internal resources and capabilities (Fernando et al., 2019; Lee et al., 2019).

For firms in emerging economies like Indonesia, where manufacturing plays a crucial role in the national economy, the challenge lies in balancing sustainability with the need for enhanced competitiveness (Agyeiwaa et al., 2024). Manufacturing firms in such economies face the dual pressure of meeting international sustainability standards while also addressing local economic constraints. The Indonesian manufacturing sector, which contributes over 20% to the country's GDP, plays a pivotal role in advancing the government's national agenda, particularly in terms of technological adoption and environmental sustainability (ERIA, 2023). This dual focus on green innovation and technological advancement is critical in Indonesia's pursuit of its "Making Indonesia 4.0" roadmap, which emphasizes sustainable, low-carbon industrialization (Cabrilo & Dahms, 2020; Choudhury, 2010). The successful implementation of these strategies, however, is contingent on firms' ability to integrate them into their existing capabilities and respond to a rapidly evolving competitive landscape.

Despite the individual contributions of green product innovation, R&D, AI adoption, intellectual capital, and government support to competitive advantage, there is limited empirical research examining how these factors interact within a unified framework, especially in the context of manufacturing firms in emerging economies. Existing studies have often treated these elements in isolation, failing to explore how they jointly shape a firm's ability to innovate and compete in dynamic environments (Afeltra et al., 2022; Mehmood, 2024). Prior studies have separately examined green product innovation and sustainable business performance (Xie et al., 2019), R&D-based innovation capabilities (Kotlar et al., 2014; Mahmood & Mubarik, 2020), AI adoption and digital analytics capabilities (Chen et al., 2021; Csaszar et al., 2024; Mehmood, 2024), intellectual capital and innovation performance (Cabrilo & Dahms, 2020; Desoky & Mousa, 2020), and institutional support for innovation (Dong et al., 2022). However, these studies have not sufficiently integrated green product innovation, R&D investment, and AI adoption within a single Indonesian manufacturing framework that simultaneously tests intellectual capital and government support as moderating mechanisms.

Therefore, this study aims to examine the effects of green product innovation, R&D investment, and AI adoption on competitive advantage in Indonesian manufacturing firms and to investigate whether intellectual capital and government support strengthen these relationships. The study is grounded primarily in the Natural Resource-Based View (NRBV), which explains how environmentally oriented innovation can generate sustainability-based competitive advantage, and Dynamic Capability Theory (DCT), which explains how firms develop and reconfigure innovation-related capabilities through R&D investment and AI adoption in response to changing technological and market conditions (Hart, 1995; Teece et al., 1997). Theoretically, this study contributes to the strategic management literature by integrating innovation strategies, intellectual capital, and government support into a unified framework for explaining competitive advantage in an emerging economy context. Practically, the findings are expected to provide insights for managers in designing integrated innovation strategies and for policymakers in formulating targeted support mechanisms that strengthen innovation-led competitiveness in Indonesian manufacturing firms.

## THEORETICAL BACKGROUND AND RESEARCH MODEL

The integration of sustainability, innovation strategies, intellectual capital, and government support in this study is grounded in four complementary theoretical perspectives: the Natural Resource-Based View (NRBV), Dynamic Capability Theory (DCT), the Resource-Based/Knowledge-Based View, and Institutional Theory. NRBV explains how environmentally oriented resources and capabilities enable firms to achieve competitive advantage through sustainability-based strategies, particularly green product innovation (Hart, 1995). DCT explains how firms develop, renew, and reconfigure capabilities through R&D investment and AI adoption in response to technological and market changes (Teece et al., 1997). The Resource-Based/Knowledge-Based View positions intellectual capital as a valuable, knowledge-based intangible resource that supports innovation implementation and competitive advantage (Barney, 1991; Grant, 1996). Meanwhile, Institutional Theory explains how government support, through incentives, regulations, and policy assistance, shapes firms' innovation behavior and competitiveness (DiMaggio & Powell, 1983).

These theoretical perspectives are directly linked to the hypotheses developed in this study. NRBV provides the basis for predicting that green product innovation enhances competitive advantage because environmentally oriented product design, resource efficiency, and sustainability-based differentiation can create value that is difficult for competitors to imitate (Hart, 1995; Xie et al., 2019). DCT provides the basis for predicting that R&D investment and AI adoption enhance competitive advantage because both represent firms' ability to renew, recombine, and reconfigure technological and knowledge-based capabilities in response to changing market conditions (Teece et al., 1997; Wang et al., 2023).

In this study, NRBV is specifically used to explain green product innovation. Green product innovation reflects a firm's ability to embed environmental considerations into product design, production, and market offerings, thereby creating sustainability-based differentiation and competitive advantage (Hart, 1995). Studies have shown that green product innovation can directly contribute to a firm's competitive advantage by enhancing operational efficiencies, improving regulatory compliance, and promoting market differentiation (Xie et al., 2019). By adopting green innovation strategies, firms not only address environmental concerns but also create value through cost reduction, resource optimization, and improved brand reputation. Similarly, R&D investment has long been identified as a critical enabler of innovation and long-term competitive advantage (Aldabbas & Oberholzer, 2023; Hsu & Fang, 2009). R&D drives the development of new knowledge, products, and processes that are crucial for sustaining competitive positions in rapidly changing industries (Wu et al., 2022). For instance, firms that invest in R&D can anticipate market trends, improve their technological offerings, and refine their operational processes, all of which contribute to enhanced performance.

AI adoption has emerged as another key strategy for firms looking to maintain their competitive edge. AI technologies such as machine learning, predictive analytics, and automation enable firms to process large volumes of data, optimize decision-making processes, and improve efficiency (Wang et al., 2023). In the context of manufacturing, AI can enhance product development cycles, streamline operations, and provide insights into consumer behavior, thereby facilitating more effective product positioning and market responses. The combination of these innovation strategies—green product innovation, R&D investment, and AI adoption—can significantly enhance a firm's competitive advantage. However, the success of these strategies depends on the firm's ability to build and utilize complementary intangible assets, such as intellectual capital, and align them with the firm's overall strategy.

Intellectual capital, which includes human, structural, and relational resources, plays a pivotal role in supporting the implementation of innovation strategies. Human capital, encompassing employees' knowledge, skills, and creativity, is essential for the successful deployment of green product innovations and the efficient use of R&D outcomes (Edvinsson, 1997; Sharma & Sharma, 2024). Structural capital, such as organizational routines, IT systems, and knowledge management processes, ensures that the firm can effectively integrate new technologies and innovations into its operations (Cabrilo & Dahms, 2020). Relational capital, which refers to a firm's external relationships with customers, suppliers, and partners, facilitates knowledge sharing and helps the firm gain access to complementary resources that enhance the effectiveness of its innovation strategies (Choudhury, 2010).

The moderation logic of intellectual capital differs across innovation strategies. For green product innovation, intellectual capital is expected to strengthen the effect on competitive advantage because skilled employees, organizational knowledge systems, and external collaboration enable firms to design, implement, and commercialize environmentally oriented products more effectively. For R&D investment, intellectual capital may strengthen the effect on competitive advantage by improving absorptive capacity, knowledge sharing, and the conversion of research outputs into marketable products. For AI adoption, intellectual capital may strengthen the effect on competitive advantage when employees possess digital skills, firms have supportive knowledge systems, and external partners help translate AI-based solutions into operational and strategic value (Cabrilo & Dahms, 2020; Csaszar et al., 2024; Desoky & Mousa, 2020).

Furthermore, government support is grounded in Institutional Theory, which explains how external institutions, regulations, incentives, and policy frameworks influence firms' strategic behavior. In this study, government support is positioned as an external institutional mechanism that may strengthen the relationship between innovation strategies and competitive advantage by reducing uncertainty, lowering innovation costs, and increasing the legitimacy of innovation activities (DiMaggio & Powell, 1983; Dong et al., 2022). Government policies, including subsidies, incentives, and regulations, provide the necessary infrastructure and financial support for firms to engage in R&D and adopt green technologies (Aldabbas & Oberholzer, 2023). In Indonesia, for example, the government's support for green initiatives and digital transformation is integral to the success of the manufacturing sector in meeting its sustainability goals and achieving competitiveness in the global market. Such support can reduce the barriers to innovation, particularly for firms with limited resources, and align their strategies with national development objectives.

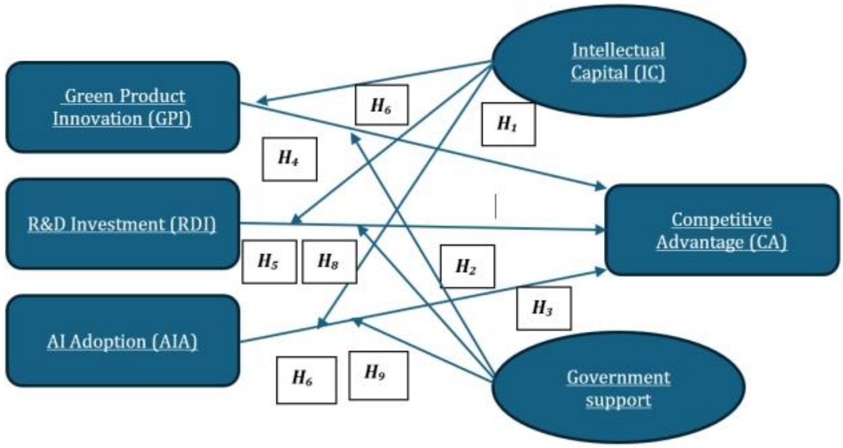
Based on the Natural Resource-Based View (NRBV), this study proposes that green product innovation positively affects competitive advantage because environmentally oriented innovation enables firms to create sustainability-based differentiation, resource efficiency, and market value (Hart, 1995; Xie et al., 2019). Accordingly, green product innovation is expected to have a positive effect on competitive advantage (H1).

Based on Dynamic Capability Theory (DCT), this study proposes that R&D investment and AI adoption positively affect competitive advantage because both reflect firms' ability to renew, recombine, and reconfigure technological and knowledge-based capabilities in response to changing market conditions (Teece et al., 1997; Wang et al., 2023). Therefore, R&D investment is expected to have a positive effect on competitive advantage (H2), and AI adoption is also expected to have a positive effect on competitive advantage (H3).

Furthermore, drawing on the Resource-Based/Knowledge-Based View, intellectual capital is expected to strengthen the relationship between innovation strategies and competitive advantage. Human capital, structural capital, and relational capital may help firms transform green product innovation, R&D investment, and AI adoption into stronger strategic outcomes through knowledge creation, organizational learning, and external collaboration (Barney, 1991; Cabrilo & Dahms, 2020; Grant, 1996). Thus, intellectual capital is expected to positively moderate the relationship between green product innovation and competitive advantage (H4), R&D investment and competitive advantage (H5), and AI adoption and competitive advantage (H6).

Finally, based on Institutional Theory, government support is expected to strengthen the relationship between innovation strategies and competitive advantage. Government incentives, subsidies, regulatory assistance, and technology-related policy support may reduce uncertainty, lower innovation costs, and increase the legitimacy of innovation activities (DiMaggio & Powell, 1983; Dong et al., 2022). Therefore, government support is expected to positively moderate the relationship between green product innovation and competitive advantage (H7), R&D investment and competitive advantage (H8), and AI adoption and competitive advantage (H9).

The research model presented in Figure 1 summarizes the proposed relationships among green product innovation, R&D investment, AI adoption, intellectual capital, government support, and competitive advantage. The model positions green product innovation, R&D investment, and AI adoption as direct predictors of competitive advantage, while intellectual capital and government support are positioned as moderating variables that may strengthen these relationships.




Source: Developed by the authors based on Hart (1995), Teece et al. (1997), Cabrilo and Dahms (2020), Desoky and Mousa (2020), and Indrawati et al. (2024).
Figure 1. RESEARCH MODEL

However, the model goes beyond these direct effects by introducing the role of intellectual capital as a moderator. Intellectual capital, comprising human, structural, and relational resources, is hypothesized to enhance the relationship between innovation strategies and competitive advantage (Desoky & Mousa, 2020; Indrawati et al., 2024). Firms with strong intellectual capital are better positioned to leverage their innovation investments, turning them into sustainable competitive advantages. Human capital, in particular, facilitates the effective implementation of green innovations and R&D outputs, while structural capital ensures that these innovations are embedded into the firm's processes (Awad, 2024; Csaszar et al., 2024). Relational capital fosters external partnerships that can accelerate the diffusion and commercialization of new products and technologies.

Furthermore, the model incorporates government support as an additional moderator. Government policies, including incentives, subsidies, and regulatory frameworks, are crucial in facilitating the implementation of green product innovation, R&D, and AI adoption. Government support helps to reduce the resource constraints that many firms face, particularly in emerging economies like Indonesia, and aligns their strategies with national development priorities such as environmental sustainability and digital transformation.

This research model is designed to examine the combined effects of these factors and provide insights into how firms can integrate internal capabilities with external support to enhance their competitiveness. By focusing on the Indonesian manufacturing sector, this model offers valuable empirical evidence on how innovation strategies, supported by intellectual capital and government policies, can create long-term competitive advantage in a rapidly changing business environment.

## RESEARCH METHODS

This study adopts a quantitative approach with a causal-explanatory research design aimed at examining the direct effects of green product innovation, R&D investment, and AI adoption on competitive advantage, with intellectual capital and government support serving as moderating variables. The central focus of this research is to assess how these variables interact and influence competitive advantage in the context of Indonesian manufacturing firms. The objective is not only to evaluate the individual contributions of innovation strategies but also to explore how intellectual capital and government support amplify or dampen these effects.

The study investigates three key independent variables: green product innovation, R&D investment, and AI adoption. These are expected to directly influence competitive advantage, with intellectual capital and government support modeled as moderators that may strengthen or weaken these direct relationships. By focusing on these variables, the study contributes to the growing body of research on how firms, particularly in emerging economies, can leverage innovation strategies alongside intangible resources and external support to build and sustain a competitive advantage (Indrawati et al., 2024; Mehmood, 2024). The conceptual framework of this study is rooted in an integrated theoretical perspective consisting of the Natural Resource-Based View, Dynamic Capability Theory, the Resource-Based/Knowledge-Based View, and Institutional Theory. NRBV explains the role of green product innovation as a sustainability-oriented capability (Hart, 1995), DCT explains the strategic relevance of R&D investment and AI adoption as dynamic capabilities (Teece et al., 1997), the Resource-Based/Knowledge-Based View explains intellectual capital as an internal knowledge-based resource (Barney, 1991; Grant, 1996), and Institutional Theory explains government support as an external institutional mechanism that shapes innovation-driven competitive advantage (DiMaggio & Powell, 1983).

Given the complexity of the relationships being modeled, including moderating effects, this study employs Partial Least Squares Structural Equation Modeling (PLS-SEM) as the primary analytical method. PLS-SEM was selected due to its flexibility in handling complex models with multiple latent constructs and interaction terms. Additionally, PLS-SEM is particularly suited for small sample sizes and non-normal data distributions, which makes it an appropriate choice for this study, where a final sample of 103 valid managerial responses representing 60 manufacturing firms was used. Unlike covariance-based SEM (CB-SEM), PLS-SEM's variance-based approach enables the simultaneous estimation of both direct and moderating effects, even in the presence of complex interrelationships (W. Chen, 2023; Musetti et al., 2023). This advantage is especially valuable for exploratory studies that seek to test theoretical models with multiple constructs and moderating effects, as in the present study.

**Sampling and Data Collection**

The population for this study consists of manufacturing firms operating in Indonesia. These firms were selected due to their central role in Indonesia's industrial economy, which is key to the nation's "Making Indonesia 4.0" roadmap, which emphasizes technological advancement and sustainability. A purposive sampling technique was used to select firms actively engaged in R&D, green product innovation, and AI adoption, ensuring that the sample represented firms that are directly involved in strategic innovation. The purposive sampling method is well-suited for studies focusing on specific industry characteristics, as it enables the selection of respondents with direct experience and knowledge of the constructs being measured (Muftiasa et al., 2023; Musetti et al., 2023).

The purposive sampling criteria were defined as follows: first, the firm had to operate in the manufacturing sector in Indonesia; second, the firm had to have ongoing or recently implemented activities related to green product innovation, R&D investment, or AI adoption; third, the respondent had to occupy a managerial or supervisory position with sufficient knowledge of the firm's innovation, technology, and strategic practices; and fourth, the respondent had to be directly or indirectly involved in decision-making, implementation, or evaluation of innovation-related activities. These criteria were applied to ensure that the respondents were able to provide relevant and informed assessments of the constructs examined in this study.

The sample comprised managerial-level professionals from various manufacturing sectors, including food and beverages, textiles, chemicals, and machinery. These individuals were chosen for their direct involvement in the firms' innovation, technology, and strategy implementation processes. A total of 180 questionnaires were distributed to managerial-level respondents in Indonesian manufacturing firms. Of these, 109 questionnaires were returned, and after data screening, 103 responses were considered valid and used for further analysis. Thus, the final sample consisted of 103 managerial and

supervisory-level respondents representing 60 manufacturing firms, with a valid response rate of 57.2% from the distributed questionnaires and 94.5% from the returned questionnaires, which is considered sufficient for conducting PLS-SEM analysis (Hair et al., 2021).
The data collection process involved the use of a structured electronic questionnaire, developed by adapting validated instruments from prior studies (Chen & Chen, 2021; Mahmood & Mubarik, 2020). The questionnaire included multiple items for each of the six constructs being studied: green product innovation, R&D investment, AI adoption, intellectual capital, government support, and competitive advantage. Each item was rated on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). Thus, higher scores indicated stronger respondent agreement with the statements measuring each construct. The development of the questionnaire also involved a pilot test conducted with a small group of industry practitioners and academic experts to refine item clarity, translation accuracy, and contextual relevance. Feedback from the pilot test led to minor adjustments in the questionnaire before full-scale distribution. Because the data were collected using a single questionnaire source, common method bias was assessed using Harman's single-factor test. The result showed that the first unrotated factor accounted for 37% of the total variance, which was below the recommended threshold of 50%. This indicates that common method bias was not a serious concern in this study.

**Operational Definitions and Indicators**
Table 1 outlines the operational definitions and indicators used in this study. Each of the six key variables was measured using established constructs adapted from previous research, ensuring that the indicators used are both conceptually consistent and empirically valid. All indicators were measured using a five-point Likert scale ranging from 1 = strongly disagree to 5 = strongly agree. This scale was used to capture respondents' perceptions of innovation strategies, intellectual capital, government support, and competitive advantage in their firms.

**Table 1.**
**OPERATIONAL DEFINITIONS AND INDICATORS OF RESEARCH VARIABLES**

| Construct | Operational Definition | Indicators | Source |
|---|---|---|---|
| **Green Product Innovation (GPI)** | Development of products designed to reduce environmental impact throughout their lifecycle | Eco-friendly design, low-emission production, recyclable packaging | Cabrilo & Dahms (2020) |
| **R&D Investment (RDI)** | Investment in knowledge creation aimed at supporting innovation in products or processes | R&D budget intensity, number of research projects, size of innovation teams | Mahmood & Mubarik (2020); Kotlar et al. (2014) |
| **AI Adoption (AIA)** | Use of AI-based systems to support operational decision-making and customer engagement | Use of machine learning, automation of business processes, AI-supported analytics | Chen et al. (2021); Csaszar et al. (2024) |
| **Intellectual Capital (IC)** | Collective intangible resources, including human, structural, and relational capital | Employee skills, IT systems, external collaboration | Cabrilo & Dahms (2020); Desoky & Mousa (2020) |
| **Competitive Advantage (CA)** | The firm's ability to outperform its competitors in the market | Customer loyalty, innovation leadership, cost advantage | Barney (1991) |

| Construct | Operational Definition | Indicators | Source |
|---|---|---|---|
| **Government Support (GS)** | External assistance in the form of policies, subsidies, and regulations | Government subsidies, policy incentives, regulatory support for sustainable practices | Desoky & Mousa (2020) |

Source: Adapted by the authors from Mahmood and Mubarik (2020), Kotlar et al. (2014), Chen et al. (2021), Csaszar et al. (2024), Cabrilo and Dahms (2020), Desoky and Mousa (2020), Barney (1991)

### Measurement Model and Validity

To ensure the validity and reliability of the constructs, confirmatory factor analysis (CFA) was conducted, following the recommendations of Hair et al. (2021). Composite reliability (CR) and Cronbach's alpha (CA) values were used to assess internal consistency, with all values exceeding the recommended threshold of 0.70. Convergent validity was evaluated using Average Variance Extracted (AVE) values, which were found to exceed the acceptable level of 0.50 for all constructs. The measurement model was further evaluated for discriminant validity, using the Heterotrait-Monotrait Ratio (HTMT), which confirmed that the constructs were empirically distinct from each other.

### Data Analysis and Moderation Testing

Data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS software. This method was chosen due to its flexibility in modeling complex relationships and handling moderating effects. The analysis was conducted in two stages: first, the measurement model was evaluated for reliability and validity, followed by the evaluation of the structural model to test the hypothesized relationships. Interaction terms between the moderators (intellectual capital and government support) and each of the independent variables were created in SmartPLS to assess the moderating effects.

Bootstrapping procedures were employed to assess the significance of the interaction terms, and simple slopes analysis was used to interpret significant moderation effects. This methodological design ensures a robust test of the hypothesized relationships and the moderating role of intellectual capital and government support.

## ANALYSIS AND RESULTS

This research gathered valid data from 103 managers and supervisory-level respondents representing 60 manufacturing firms in Indonesia, representing a range of industrial sectors such as automotive, electronics, food and beverage, pharmaceuticals, textiles, petrochemicals, extractive and energy, and building materials. The diversity of sectors provides a broader perspective on innovation strategies and competitive advantage within Indonesian manufacturing firms. (refer to Table 2).

**Table 2.**
**INDUSTRIAL SECTOR DISTRIBUTION OF THE 103 VALID MANAGERIAL RESPONDENTS REPRESENTING 60 MANUFACTURING FIRMS**

| No | Sector | Frequency | Percentage (%) |
|---|---|---|---|
| 1 | Motor vehicle industry | 16 | 15.0 |
| 2 | Electronic goods sector | 12 | 11.7 |
| 3 | Beverage and food manufacturing sector | 17 | 16.7 |
| 4 | Pharmaceutical and herbal industry | 15 | 15.0 |
| 5 | Textile products and accessories industry | 15 | 15.0 |
| 6 | Petrochemical and chemical manufacturing sector | 12 | 11.7 |
| 7 | Extractive and energy industry | 12 | 11.7 |

| No | Sector | Frequency | Percentage (%) |
|---|---|---|---|
| 8 | Building materials sector | 4 | 3.2 |
| | **Total** | **103** | **100** |

Source: Primary data processed by the authors (2026)

Based on the 60 firms represented in the sample, the majority focused on green product innovation, accounting for 46.7% of the firms, followed by R&D investment at 36.7% and AI adoption at 16.6%. These percentages approximately represent 28 firms prioritizing green product innovation, 22 firms prioritizing R&D investment, and 10 firms prioritizing AI adoption. This distribution illustrates a growing tendency among Indonesian manufacturing firms to address environmental and technological challenges through targeted innovation strategies.

Table 3 presents the demographic details of the managerial respondents. The majority of the respondents were in supervisory positions, with 37 managers (35.9%) in upper management roles and 35 managers (34.0%) in lower management roles. Mid-level managers accounted for 9 respondents (8.7%), while senior executives comprised only 2 respondents (1.9%). This suggests that the responses predominantly came from managers involved in day-to-day operations rather than from top leadership.

In terms of tenure, a substantial portion of the managers (61 respondents, 59.2%) had worked in their firms for four to six years, implying they possessed a considerable understanding of the organization. In contrast, only 2 respondents (1.9%) reported having more than ten years of tenure, indicating that most participants were relatively newer to their managerial positions.

Regarding the size of the firms, the majority of respondents came from large organizations with over 200 employees (60 respondents, 58.3%), followed by medium-sized companies (37 respondents, 35.9%), and a small number from small-sized firms (6 respondents, 5.8%).

Finally, geographically, most of the respondents were located in Jakarta (53 respondents, 51.5%), with smaller groups situated in Surabaya (19 respondents, 18.4%), Banten (14 respondents, 13.6%), Bandung (12 respondents, 11.7%), and Bekasi (5 respondents, 4.8%). This highlights the importance of urban industrial centers in shaping innovation strategies.

**Table 3.**
**DEMOGRAPHIC CHARACTERISTICS OF RESPONDENTS**

| Demographic Category | Classification | Frequency | Percentage (%) |
|---|---|---|---|
| **Level of Management** | Executive management | 2 | 1.9 |
| | Mid-level management | 9 | 8.7 |
| | First-line management | 35 | 34.0 |
| | Senior supervisor | 37 | 35.9 |
| | Junior supervisor | 20 | 19.4 |
| **Work tenure** | Less than 4 years | 31 | 30.1 |
| | 4 to 6 years | 61 | 59.2 |
| | 7 to 10 years | 9 | 8.7 |
| | More than 10 years | 2 | 1.9 |
| **Company size** | Large enterprises (>200 employees) | 60 | 58.3 |
| | Medium enterprises (51–200 employees) | 37 | 35.9 |
| | Small enterprises (1–50 employees) | 6 | 5.8 |
| **Location (Top 5)** | Jakarta | 53 | 51.5 |

| Demographic Category | Classification | Frequency | Percentage (%) |
|---|---|---|---|
| | Surabaya | 19 | 18.4 |
| | Banten | 14 | 13.6 |
| | Bandung | 12 | 11.7 |
| | Bekasi | 5 | 4.8 |

Source: Primary data processed by the authors (2026)

## RESULTS

### Measurement Model Evaluation

The measurement model was evaluated through indicator reliability, internal consistency reliability, convergent validity, and discriminant validity. All outer loadings exceeded the recommended threshold of 0.70, indicating adequate indicator reliability. Composite Reliability values were above 0.70, confirming internal consistency reliability. In addition, the Average Variance Extracted values exceeded 0.50, supporting convergent validity. Discriminant validity was assessed using the HTMT ratio, and all values were below 0.85, indicating that the constructs were empirically distinct (Hair et al., 2021).

**Table 4.**
**MEASUREMENT MODEL, LOADING, CONSTRUCT RELIABILITY, AND CONVERGENT VALIDITY**

| Construct | Item | Loading (>0.5) | Cronbach's Alpha (CA) | Composite Reliability (CR) | Average Variance Extracted (AVE) |
|---|---|---|---|---|---|
| **Green Product Innovation (GPI)** | GPI1 | 0.737 | 0.879 | 0.905 | 0.657 |
| | GPI2 | 0.849 | | | |
| | GPI3 | 0.818 | | | |
| | GPI4 | 0.740 | | | |
| | GPI5 | 0.897 | | | |
| **Investment in R&D (RDI)** | RD1 | 0.746 | 0.865 | 0.910 | 0.670 |
| | RD2 | 0.843 | | | |
| | RD3 | 0.778 | | | |
| | RD4 | 0.894 | | | |
| | RD5 | 0.823 | | | |
| **Adoption of AI (AIA)** | AIA1 | 0.811 | 0.846 | 0.900 | 0.644 |
| | AIA2 | 0.752 | | | |
| | AIA3 | 0.757 | | | |
| | AIA4 | 0.785 | | | |
| | AIA5 | 0.898 | | | |
| **Intellectual Capital (IC)** | IC1 | 0.793 | 0.801 | 0.901 | 0.647 |
| | IC2 | 0.853 | | | |
| | IC3 | 0.791 | | | |
| | IC4 | 0.747 | | | |
| | IC5 | 0.834 | | | |

| Construct | Item | Loading (>0.5) | Cronbach's Alpha (CA) | Composite Reliability (CR) | Average Variance Extracted (AVE) |
|---|---|---|---|---|---|
| **Competitive Advantage (CA)** | CA1 | 0.759 | 0.861 | 0.928 | 0.618 |
| | CA2 | 0.824 | | | |
| | CA3 | 0.898 | | | |
| | CA4 | 0.729 | | | |
| | CA5 | 0.793 | | | |
| | CA6 | 0.713 | | | |
| | CA7 | 0.745 | | | |
| | CA8 | 0.811 | | | |
| **Government Support (GS)** | GS1 | 0.765 | 0.733 | 0.833 | 0.624 |
| | GS2 | 0.792 | | | |
| | GS3 | 0.812 | | | |

Source: SmartPLS output based on primary data processed by the authors (2026)

**Structural Model Evaluation**

Next, the structural model was assessed through various diagnostics, including collinearity, $R^2$, effect size ($f^2$), $Q^2$, and model fit indices. The Variance Inflation Factor (VIF) values were all below the threshold of 5 (range: 1.231–2.873), indicating no multicollinearity issues. The model's explanatory power was substantial, with $R^2$ for competitive advantage reaching 0.665, meaning 66.5% of the variance in competitive advantage is explained by green product innovation, R&D investment, AI adoption, and the moderating variables, namely intellectual capital and government support. This $R^2$ value indicates that the model has strong explanatory power in explaining competitive advantage.

The effect size ($f^2$) ranged from 0.075 to 0.182, suggesting that the independent variables (green product innovation, R&D investment, and AI adoption) and the moderators (intellectual capital and government support) collectively have a small to medium effects on competitive advantage. The predictive relevance ($Q^2$) was 0.233, indicating acceptable out-of-sample predictive power. A $Q^2$ value above zero indicates that the model has predictive relevance for the endogenous construct. The Standardized Root Mean Square Residual (SRMR) was calculated at 0.042, which is well below the threshold of 0.08, confirming that the model fits the data well and supports the validity of the structural model. Thus, the SRMR result indicates an acceptable overall model fit (Hair et al., 2021).

**Path Coefficients and Hypothesis Testing**

Discriminant validity was assessed using the Heterotrait-Monotrait Ratio (HTMT). As shown in Table 5, all HTMT values range from 0.253 to 0.816, which are below the conservative threshold of 0.85. These results indicate that the constructs are empirically distinct and that discriminant validity is established (Hair et al., 2021).

**Table 5.**
**Discriminant Validity Assessment Using HTMT Ratio**

| Construct | Adoption of AI (AIA) | Government Support (GS) | Green Product Innovation (GPI) | Intellectual Capital (IC) | Investment in R&D (RDI) |
|---|---|---|---|---|---|
| **Adoption of AI (AIA)** | - | | | | |

| Construct | Adoption of AI (AIA) | Government Support (GS) | Green Product Innovation (GPI) | Intellectual Capital (IC) | Investment in R&D (RDI) |
|---|---|---|---|---|---|
| **Government Support (GS)** | 0.253 | - | | | |
| **Green Product Innovation (GPI)** | 0.816 | 0.704 | - | | |
| **Intellectual Capital (IC)** | 0.688 | 0.462 | 0.713 | - | |
| **Investment in R&D (RDI)** | 0.487 | 0.300 | 0.678 | 0.687 | - |

Source: SmartPLS output based on primary data processed by the authors (2026)

The results of hypothesis testing presented in Table 6 show that green product innovation, R&D investment, and AI adoption have positive and significant effects on competitive advantage. Green product innovation has the strongest direct effect on competitive advantage ($\beta = 0.357$, $t = 4.502$, $p < 0.001$), supporting H1. R&D investment also has a significant positive effect on competitive advantage ($\beta = 0.278$, $t = 3.874$, $p < 0.001$), supporting H2. Similarly, AI adoption positively affects competitive advantage ($\beta = 0.246$, $t = 3.704$, $p < 0.001$), supporting H3. These findings indicate that innovation strategies, whether sustainability-oriented, knowledge-based, or technology-driven, contribute to strengthening firms' competitive positions in the Indonesian manufacturing sector.

The moderation analysis provides more nuanced findings. Intellectual capital significantly moderates the relationship between green product innovation and competitive advantage ($\beta = 0.103$, $t = 4.500$, $p < 0.001$), supporting H4. This suggests that firms with stronger intellectual capital are better able to convert green product innovation into competitive advantage. However, intellectual capital does not significantly moderate the relationship between R&D investment and competitive advantage ($\beta = 0.152$, $t = 1.041$, $p = 0.134$), meaning that H5 is not supported. Intellectual capital also does not significantly moderate the relationship between AI adoption and competitive advantage ($\beta = 0.035$, $t = 1.041$, $p = 0.143$), so H6 is not supported.

In terms of government support, the results show that government support significantly moderates the relationship between green product innovation and competitive advantage ($\beta = 0.123$, $t = 3.410$, $p < 0.001$), supporting H7. Government support also significantly strengthens the relationship between R&D investment and competitive advantage ($\beta = 0.142$, $t = 3.975$, $p < 0.001$), supporting H8. However, government support does not significantly moderate the relationship between AI adoption and competitive advantage ($\beta = 0.036$, $t = 1.455$, $p = 0.133$), indicating that H9 is not supported. Overall, the findings demonstrate that intellectual capital and government support play selective moderating roles rather than uniformly strengthening all innovation strategies.

**Table 6.**
**SUMMARY OF HYPOTHESIS TESTING RESULTS**

| Hypothesis | Path | B | t-value | p-value | Decision |
|---|---|---|---|---|---|
| H1 | Green Product Innovation → Competitive Advantage | 0.357 | 4.502 | <0.001 | Supported |
| H2 | Investment in R&D → Competitive Advantage | 0.278 | 3.874 | <0.001 | Supported |

| Hypothesis | Path | B | t-value | p-value | Decision |
|---|---|---|---|---|---|
| H3 | AI Adoption → Competitive Advantage | 0.246 | 3.704 | <0.001 | Supported |
| H4 | Green Product Innovation × Intellectual Capital → Competitive Advantage | 0.103 | 4.500 | <0.001 | Supported |
| H5 | R&D Investment × Intellectual Capital → Competitive Advantage | 0.152 | 1.041 | 0.134 | Not Supported |
| H6 | AI Adoption × Intellectual Capital → Competitive Advantage | 0.035 | 1.041 | 0.143 | Not Supported |
| H7 | Green Product Innovation × Government Support → Competitive Advantage | 0.123 | 3.410 | <0.001 | Supported |
| H8 | R&D Investment × Government Support → Competitive Advantage | 0.142 | 3.975 | <0.001 | Supported |
| H9 | AI Adoption × Government Support → Competitive Advantage | 0.036 | 1.455 | 0.133 | Not Supported |

Source: SmartPLS bootstrapping output based on primary data processed by the authors (2026)

## DISCUSSION

This study provides three main findings. First, green product innovation, R&D investment, and AI adoption have positive and significant effects on competitive advantage. Second, intellectual capital significantly strengthens only the relationship between green product innovation and competitive advantage, while its moderating effects on R&D investment and AI adoption are not significant. Third, government support significantly strengthens the effects of green product innovation and R&D investment on competitive advantage, but does not significantly strengthen the effect of AI adoption. Overall, H1, H2, H3, H4, H7, and H8 are supported, whereas H5, H6, and H9 are not supported. These results indicate that innovation strategies directly enhance competitive advantage, while intellectual capital and government support operate as selective rather than universal moderating mechanisms.

Before discussing each hypothesis, the overall model diagnostics indicate that the proposed model is statistically adequate. The $R^2$ value of 0.665 shows that 66.5% of the variance in competitive advantage is explained by green product innovation, R&D investment, AI adoption, intellectual capital, and government support, indicating strong explanatory power. The $Q^2$ value of 0.233 is above zero, showing that the model has acceptable predictive relevance. In addition, the SRMR value of 0.042 is below the recommended threshold of 0.08, indicating acceptable model fit (Hair et al., 2021).

For the supported hypotheses, the positive effect of green product innovation on competitive advantage supports H1 and is consistent with the Natural Resource-Based View (NRBV). NRBV argues that environmentally oriented capabilities can create sustainability-based differentiation and long-term competitive advantage. This finding confirms previous studies showing that green innovation improves competitive performance through resource efficiency, regulatory responsiveness, and market differentiation (Garcia et al., 2019; Rehman et al., 2021; Xie et al., 2019). This evidence supports the argument that green innovation is not just a compliance-driven initiative but a strategic pathway that contributes to long-term competitive strength. In the Indonesian manufacturing context, eco-friendly product design, low-emission production, and recyclable packaging appear to strengthen firms' competitive position in markets increasingly influenced by sustainability expectations.

The positive effect of R&D investment on competitive advantage supports H2 and aligns with Dynamic Capability Theory (DCT). DCT explains that firms gain competitiveness by renewing, recombining, and reconfiguring knowledge and technological capabilities in response to market change (Teece et al, 1997). This result confirms prior research indicating that R&D capability supports innovation outcomes and competitive advantage (Aldabbas & Oberholzer, 2023; Kotlar et al., 2014; Mahmood & Mubarik, 2020). Thus, R&D investment remains an important mechanism for manufacturing firms to improve products, processes, and technological responsiveness.

The positive effect of AI adoption on competitive advantage supports H3 and also reflects DCT. AI adoption enables firms to improve analytics, automation, decision-making, and operational responsiveness, which can strengthen competitive advantage. This finding is consistent with Wang et al. (2023) and Csaszar et al. (2024), who emphasized the strategic role of AI in improving decision quality and organizational competitiveness. However, the relatively smaller coefficient of AI adoption compared with green product innovation suggests that AI-based competitiveness in Indonesian manufacturing may still depend on digital infrastructure, data quality, and organizational readiness.

The significant moderating effect of intellectual capital on the relationship between green product innovation and competitive advantage supports H4. This finding is consistent with the Resource-Based/Knowledge-Based View, which positions human capital, structural capital, and relational capital as intangible resources that help firms convert innovation into strategic value (Barney, 1991; Grant, 1996). This result confirms Cabrilo and Dahms (2020) and Desoky and Mousa (2020), who found that intellectual capital supports innovation performance through employee knowledge, organizational systems, and external collaboration. In this study, intellectual capital helps firms transform green product innovation into market differentiation, operational efficiency, and sustainability-based positioning.

Government support significantly strengthens the relationship between green product innovation and competitive advantage, supporting H7. This finding is consistent with Institutional Theory, which explains that external institutional mechanisms can reduce uncertainty, provide legitimacy, and lower innovation costs (DiMaggio & Powell, 1983). It also confirms Dong et al. (2022), who showed that institutional support can strengthen green innovation outcomes. In Indonesia, environmental incentives, regulatory guidance, subsidies, and technical assistance may help manufacturing firms implement green product innovation more effectively.

Government support also significantly strengthens the relationship between R&D investment and competitive advantage, supporting H8. This finding confirms previous research suggesting that policy incentives, innovation grants, tax support, and collaborative research programs can improve the competitive returns of R&D investment (Dong et al., 2022). Institutionally, this means that government support helps reduce financial constraints and encourages firms to sustain research-based innovation.

For the unsupported hypotheses, intellectual capital does not significantly moderate the relationship between R&D investment and competitive advantage ($\beta = 0.152$, $t = 1.041$, $p = 0.134$), indicating that H5 is not supported. This result suggests that general intellectual capital may not be sufficient to convert R&D investment into competitive advantage. R&D outcomes may require more specific complementary capabilities, such as absorptive capacity, commercialization capability, research management systems, and technology transfer mechanisms. Therefore, this finding partly contradicts studies that emphasize the broad role of intellectual capital in innovation performance, but it refines this argument by showing that R&D requires more specialized innovation-conversion capabilities.

Intellectual capital also does not significantly moderate the relationship between AI adoption and competitive advantage ($\beta = 0.035$, $t = 1.041$, $p = 0.143$), indicating that H6 is not supported. This suggests that AI adoption requires digital capabilities that differ from traditional intellectual capital, such as data governance, algorithmic capability, digital infrastructure, cybersecurity readiness, and digital transformation leadership.

Government support does not significantly moderate the relationship between AI adoption and competitive advantage (β = 0.036, t = 1.455, p = 0.133), indicating that H9 is not supported. This result suggests that general government support may be sufficient to encourage green innovation and R&D, but not enough to accelerate AI-based transformation. AI adoption requires more targeted institutional arrangements, including digital infrastructure policy, AI talent development, data governance frameworks, public–private technology collaboration, and industry-specific AI programs. Thus, this finding extends Institutional Theory by showing that institutional support must be specific to the type of innovation being implemented.

Taken together, these findings explicitly support NRBV and DCT while refining the Resource-Based/Knowledge-Based View and Institutional Theory. Green product innovation confirms NRBV because sustainability-oriented capabilities enhance competitive advantage. R&D investment and AI adoption confirm DCT because technological renewal and capability reconfiguration improve firm competitiveness. However, the unsupported moderating effects of intellectual capital and government support on AI adoption show that digital transformation requires more specialized capabilities and policy instruments than traditional innovation strategies.

## CONCLUSIONS

This study examines the effects of green product innovation, R&D investment, and AI adoption on competitive advantage in Indonesian manufacturing firms, while also investigating the moderating roles of intellectual capital and government support. The findings confirm that green product innovation, R&D investment, and AI adoption each have a positive and significant effect on competitive advantage. Among these innovation strategies, green product innovation shows the strongest effect, followed by R&D investment and AI adoption. This indicates that sustainability-oriented innovation, knowledge creation, and digital technology adoption are important strategic drivers of competitiveness in the manufacturing sector.

The moderation results reveal that intellectual capital and government support do not strengthen all innovation strategies equally. Intellectual capital significantly strengthens the relationship between green product innovation and competitive advantage, suggesting that human, structural, and relational capital help firms transform green innovation into stronger market positioning. However, intellectual capital does not significantly moderate the relationships between R&D investment and competitive advantage or between AI adoption and competitive advantage. These findings indicate that R&D and AI adoption may require more specific capabilities beyond general intellectual capital, such as commercialization capability, absorptive capacity, digital readiness, data infrastructure, and algorithmic expertise.

Government support significantly strengthens the effects of green product innovation and R&D investment on competitive advantage. This suggests that policy incentives, subsidies, regulatory support, and innovation programs can enhance the competitive returns of sustainability-oriented and research-based innovation. However, government support does not significantly moderate the relationship between AI adoption and competitive advantage. This finding implies that AI adoption requires more targeted forms of support, including digital infrastructure, AI talent development, data governance, and industry-specific technology programs.

Theoretically, this study contributes to the strategic management literature by showing that innovation strategies directly enhance competitive advantage, but their effectiveness is conditionally shaped by internal and external resources. The findings refine the Natural Resource-Based View, Dynamic Capability Theory, the Resource-Based/Knowledge-Based View, and Institutional Theory by demonstrating that intellectual capital and government support play selective rather than universal moderating roles in innovation-driven competitive advantage. Practically, managers should integrate green product innovation, R&D investment, and AI adoption into their competitive strategies while developing the specific capabilities required for each type of innovation. Policymakers should continue supporting green innovation and R&D while designing more focused programs to accelerate AI-based transformation in manufacturing firms.

Future research may further examine the role of digital readiness, absorptive capacity, AI capability, and data governance as potential moderators or mediators in the relationship between AI adoption and competitive advantage. Comparative studies across industries or emerging economies may also provide deeper insights into how different institutional and technological contexts shape innovation-driven competitiveness.

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