

# The Barriers of Adopting Digital Twin In Indonesian Industry: The Innovation Resistance Theory

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## ABSTRACT

This research examines barriers to digital twin adoption in Indonesian industries, by employing Innovation Resistance Theory (IRT). Indonesia's burgeoning energy demands necessitate decarbonization efforts, and digital twins offer a promising solution for improving energy efficiency to reduce emissions. However, their adoption lags. The study investigates functional (usage, value, risk) and psychological (image) barriers to adoption of digital twin. Hypotheses posit a positive relationship between each barrier and resistance to adoption of digital twin. The research also examines the moderating role of incentive policies in the relationship of each barrier and the resistance to adopt digital twin. By employing a quantitative approach with a cross-sectional survey of Indonesian industrial professionals, and PLS-SEM analysis, the study finds significant positive effects of usage, value, and risk barriers on resistance of adoption of digital twin. Image barriers show a weaker, non-significant influence. While incentive policies positively moderate the relationship between usage barriers and resistance, their impact on value and risk barriers is negative. These findings highlight the importance of addressing concerns about cost, technological superiority, and risk alongside the need for stronger, more targeted government support in addressing financial and risk-related aspects. Understanding the interplay of barriers and incentive policies is crucial for promoting digital twin uptake, fostering sustainable industrial growth in Indonesia. Further research could explore the specific contexts of various industrial sectors.

**Keywords:** digital twin, innovation resistance theory, incentive policy, decarbonization

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## INTRODUCTION

Energy is an important factor in supporting business processes in a company. As an emerging country, electricity demand in Indonesia is expected to double in the next few years (Siregar, 2024). However, with the increase in electricity demand, there is a potential increase in carbon emissions because electricity generation is a significant source of emission (Chukwunonso Bosah et al., 2020). In Indonesia, the industrial sector contributes to 34% of the national greenhouse gas (GHG) emission with 72% from the energy use. In 2023, the industrial sector emits 422 mtCO<sub>2e</sub>, from energy, waste and industrial process and product use. Without any ambitious innovation, the industrial emission is predicted to double in 2030 from the previous status in 2019 (World Resources Institute Indonesia, 2024).

To decarbonize industry, there are several measures that can be taken such as totally replacing the source of the energy from fossil fuel with renewable energy. However, since this option is yet to fully applicable in Indonesia, another measures that can be employed is improving the energy efficiency (A. Kumar et al., 2024). In 2002, Grievies introduced the concept of Digital Twin as an innovative integrated tool that offers the ability to do live tracking, simulation, exact projection and simulation (Sharma et al., 2022). In building, lighting

system consume about 20% to 60% of overall energy used (Tan et al., 2022). Hence, utilizing energy saving technology will significantly reduce the energy consumption of building.

Digital twin combines real-time simulation and forecasting ability to improve system process and maintenance by merging detailed simulation with data-driven modeling approach. Adoption of this technology can lead to significant emission reduction by improving energy system efficiency. However, this technology is not yet adopted in Indonesian industry. Therefore, it leads to the question in this research.

RQ 1: What are the primary barriers of adopting digital twin in industry in Indonesia?

RQ 2: Do incentive policies have a moderating influence on the relationship between barriers and the resistance to adopting digital twin?

According to Hafeez et al. (2024), digital twins can revolutionize industrial operations by optimizing energy efficiency and reducing emissions, but their adoption is hindered by functional barriers like high implementation costs and concerns about data security. Similarly, Xue et al. (2024) highlight that innovation resistance in industries, particularly regarding new technologies like digital twins, is largely driven by psychological barriers such as traditional perceptions and resistance to change, which can hinder adoption despite the potential benefits.

The urgency of this research lies in the pressing need for industries in Indonesia to adopt sustainable technologies such as digital twins to address decarbonization goals and improve energy efficiency. With Indonesia's growing energy demand and significant contributions to greenhouse gas emissions, embracing technologies like digital twins can play a vital role in reducing energy consumption and emissions. However, the slow adoption of this technology due to various barriers poses a significant challenge to achieving the nation's sustainability targets, making it crucial to understand the factors that contribute to resistance and to identify strategies for overcoming these obstacles.

While several studies have explored barriers to adopting new technologies in various industries, few have specifically focused on the adoption of digital twins in the context of Indonesian industries, particularly in relation to energy efficiency and decarbonization. There is also limited research on how incentive policies can moderate these barriers, making this study valuable in understanding the dynamics between functional and psychological barriers and the role of government incentives in facilitating technology adoption.

This study introduces a novel approach by applying Innovation Resistance Theory (IRT) to examine the barriers to adopting digital twin technologies in Indonesian industries, particularly in the context of energy decarbonization. By incorporating incentive policies as a moderating factor, the research provides new insights into how functional and psychological barriers interact with government interventions to influence adoption. This approach has not been extensively studied in the context of industrial decarbonization in emerging economies like Indonesia.

The primary objective of this research is to identify and analyze the functional and psychological barriers to adopting digital twin technologies in Indonesian industries and to examine the moderating role of incentive policies. The study aims to provide actionable recommendations for overcoming resistance to adoption and promoting the use of digital twins to improve energy efficiency. The benefits of this research include offering insights for policymakers to design more effective incentive programs, helping businesses understand the challenges and opportunities of adopting digital twins, and contributing to the broader goal of industrial decarbonization and sustainability.

## **Literatur Review**

### **Digital Twin**

The phrase "Digital Twin" was introduced by Dr. Michael Grieves at the University of Michigan in 2002. This technology creates virtual models of actual energy assets, facilitating real-time monitoring, simulation and improvement throughout various stages of industry

lifecycle (Koirala et al., 2024). Digital twin is created with the aim to support digital transformation and enhance decision-making process across various industrial sector (R. Kumar & Agrawal, 2024). Kaitouni et al (2023) conducted research to evaluate the effectiveness of digital twin framework as a cutting-edge information technology for optimizing the performance of solar photovoltaics (PV) systems distributed in urban areas. The finding highlights the successful incorporation of real-time surveillance and remote sensing for comprehensive condition monitoring of PV system in cities. The utilization of digital twin technology facilitates the assessment of spatiotemporal energy performance, evolution with changing environments, and identification of degradation through anomaly detection. While in Mining Industry, Nobahar et al (2024) found that certain critical parts of mining operation can be optimized by implementing digital twin by facilitating autonomous operation and augmenting safety and productivity. In addition, it can be used in production drilling to streamline the workflow, enhanced precision, and increased operational efficiency all while reducing equipment downtime (Nobahar et al., 2024).

### **Innovation Resistance Theory**

The Innovation Resistance Theory (IRT) is a reliable framework to examine consumer resistance to a newly proposed innovation (Xue et al., 2024). It provides conceptual framework for addressing resistance to adoption of novel technology. It also aids in comprehending customer resistance behavior. IRT can be described as a calculated response setting from thoughtful consideration and deliberation regarding adoption and implementation of a novel system. This behavior arises when a new system challenges the existing status quo and deviates from established routines and practices (Hossain, 2023)

Existing literature has indicated that individual can develop resistance when they adopt and employ innovation that is unlike their current state and culture (Ram & Sheth, 1989). The IRT categorizes barriers into two primary groups: functional and psychological barriers. Functional barriers encompass value, usage, and risk-related obstacles that emerge from user's understanding of the changes associated with adopting new innovations. In contrast, the psychological barriers include traditional and image-related impediments, which stem from conflicts between the innovation and customers' pre-existing beliefs or values. A brief description about those barriers is as follows: Usage Barrier (UB): This is the primary cause of resistance, occurring when new innovation clash with consumers' established routines, practices, or experiences (Chen et al., 2022). Value Barrier (VB): When an innovation fails to offer superior benefits in opposition with current choices, consumers lack motivations in embracing the change (Chen et al., 2022; Xue et al., 2024). Risk Barrier (RB): Change inherently carries an element of unknowns, potentially exposing consumers to various unforeseen risks. These risk can be classified into physical, economic, functional and social categories (Chen et al., 2022).

If the proposed technology is difficult for the user to comprehend, do not bring valuable benefit or pose a significant risk to the company, then it is not effectively supporting the company, and they are going to reject the technology. Hence, we propose this hypothesis:

**Hypothesis 1a.** Usage barrier is positively influencing the resistance to adoption of digital twin in industry.

**Hypothesis 1b.** Value barrier is positively influencing the resistance to adoption of digital twin in industry.

**Hypothesis 1c.** Risk barrier is positively influencing the resistance to adoption of digital twin in industry.

Psychological barriers surface when accepting an innovation appears to contradict established consumer notions (Kaur et al., 2020). Psychological barriers consist of tradition and image barriers. Tradition barrier shows resistance that arises when a novel idea conflicts with the custom or culture of users. The shift from familiar traditions can lead to reluctance in

adopting new ideas or products (Chen et al., 2022). Image Barrier (IB) emerges when an innovation is associated with a specific industry or country of origin that carries negative connotations (Xue et al., 2024). If consumers perceived the source of the innovation unfavorably, it can trigger resistance to adoption, regardless of the innovation’s actual merits (Chen et al., 2022). Hence, we propose this hypothesis:

**Hypothesis 2.** Image barrier is positively influencing the resistance to adoption of digital twin in industry.

Due to limited valid response on tradition barrier, this research does not adopt tradition barrier on the framework

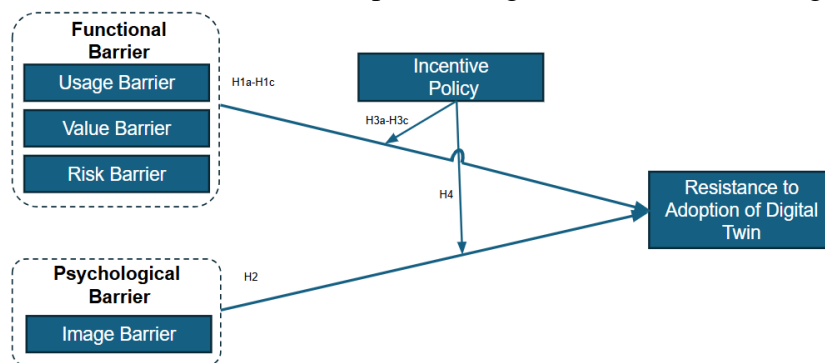
**Incentive Policy**

Incentive policies for decarbonization in the Indonesian industrial context have become more increasingly important as the country strive to meet its climate commitments. Several policies and regulations are provided to encourage companies to reduce their carbon footprint, particularly through energy efficiency measures. The government introduced the Presidential Regulation no 98/2021 that discusses carbon pricing mechanisms, including carbon tax and cap-and-trade system, which incentivizes companies to reduce their emission or to adopt low-carbon technologies and improve energy efficiency. In terms of tax incentive, the government offers tax allowances and tax holidays for investment in energy-efficient technology. In terms of green financing, The Indonesian Financial Service Authority (OJK) has introduced the roadmap of Sustainable Finance which encourages banks to provide preferential loans for green projects, including those focused on energy efficiency and emission reduction. Lastly, the Government Regulation no 70/2009 mandates energy management systems for large energy consumers and provides incentives for energy conservation efforts. All of these regulations aim to promote efficient energy use and reduce energy consumption. Hence, we propose this hypothesis:

**Hypothesis 3a-c:** The relationship between functional barriers and the resistance to adoption of digital twin will be positively moderated by incentive policy.

**Hypothesis 4:** The relationship between psychological barriers and the resistance to adoption of digital twin will be positively moderated by incentive policy.

In summary, the theoretical model of the relationship between functional barrier and psychological barrier and the resistance to adoption of digital twin is shown in figure 1.



**Figure 1. Theoretical Model**

**METHOD**

This research is a hypothesis testing research that seeks to investigate the impact of the functional and psychological barriers to the resistance to adopting digital twin by using quantitative research. The hypothesis testing is causal in nature because it aims to identify the causal influence between functional barriers and psychological barrier on the adoption of digital twin. The research was conducted in cross-sectional design on which all information was collected in one single time by answering questionnaire provided. To generate data, this

research used purposive non-probability sampling because it has some criteria such as (i) individuals that work in Indonesian industry, private and state-owned enterprise (SOEs) that is listed and not-listed in Indonesian Stock Exchange. The questionnaire was made online using google form and the link shared using snowball technique through social media such as Whatsapp and Instagram.

The independent variables consisted of functional barriers which include usage, value, risk barriers and psychological barriers which only image barrier. The moderating variable was the incentive policy. Lastly, the dependent variable was the resistance to adopt digital twin. The variable measurement was conducted using indicators that were adapted from previous researchs into statements that shown in the table 1 below:

**Table 1. Constructs of Questions Provided in the Questionnaires**

|                                                                          |        |                                                                                                                                                              |
|--------------------------------------------------------------------------|--------|--------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Usage Barrier (UB)<br>(Laukkanen, 2016; Xue et al., 2024)                | UB 1   | I understand that Digital Twin for decarbonization is convenient to be utilized in our business.                                                             |
|                                                                          | UB 2   | I believe the implementation of digital twin for decarbonization is pleasant to be utilized in our business                                                  |
|                                                                          | UB 3   | I believe it is expedient to transition from current business operation to the usage of the digital twin to decarbonize our system.                          |
| Value Barrier (VB) (Ram & Sheth, 1989)                                   | VB1    | In my opinion, our current business technologies (conventional) are more environmentally friendly than the digital twin that are currently offered in market |
|                                                                          | VB 2   | In my understanding, digital twin can enhance energy efficiency.                                                                                             |
|                                                                          | VB 3   | In my view, digital twin can reduce carbon emission                                                                                                          |
| Risk Barrier (RB) (Xue et al., 2024)                                     | RB 1   | I am worried that the longevity of the digital twin is insufficient.                                                                                         |
|                                                                          | RB 2   | I am worried regarding the security of digital twin to our business                                                                                          |
|                                                                          | RB 3   | I am worried that the service interval of the digital twin is excessively high.                                                                              |
|                                                                          | RB 4   | I am worried over the inconvenience resulting from the limited supply of the spare parts needed for repairs by the manufacturer.                             |
| Image Barrier (IB) (Ram & Sheth, 1989; C. L. Wang et al., 2012)          | IB 1   | I do not believe the digital twin technology as it is not created by Indonesian                                                                              |
|                                                                          | IB 2   | I possess an image indicating that the digital twin will bring challenge as it is adopted from western country                                               |
| Incentive Policy (IP) (X.-W. Wang et al., 2021) (Rajendran et al., 2019) | IP 1   | I think government subsidies have a promoting effect on our business operation decision                                                                      |
|                                                                          | IP 2   | I believe that tax reduction and exemption will positively influence our decision to invest in digital twin technology for decarbonization efforts.          |
|                                                                          | IP 3   | One of reason why we utilize digital twin for decarbonization is due to the incentive policy                                                                 |
|                                                                          | IP 4   | The government's support for the company that do decarbonization action is one of the reason why we utilize digital twin for decarbonization                 |
| Resistance to Digital Twin                                               | RDTA 1 | If it can fulfill the requirements, I will propose acquiring the technology.                                                                                 |

|                 |           |                                                                                                                           |
|-----------------|-----------|---------------------------------------------------------------------------------------------------------------------------|
| Adoption (RDTA) | RDTA<br>2 | I will recommend the use of digital twin to friends in other company                                                      |
|                 | RDTA<br>3 | There is a strong likelihood that I will opt for digital twin when presented with a chance for technological advancement. |

**RESULTS AND DISCUSSION**

**Validity Test**

The research used PLS-SEM to evaluate measurement and structural models. In the convergent validity, the variance inflation factor (AVE) and the loading factor were tested. Variable is considered valid if the AVE is greater than 0.5 and factor loading is greater than 0.7 (Ghozali & Latan, 2015:74). It was found that the AVE of UB, VB, RB, IB, and IP were 0.8, 0.84, 0.64, 0.77, and 0.66 consecutively. The AVE of UB\*IP, VB\*IP, RB\*IP, IB\*IP and RDTA were 1, 0.84, 1, 1, and 0.76 consecutively. Hence, each variable was considered valid.

Next, analysis was conducted to evaluate the factor loading. An indicator has good reliability if the factor loading is >0.70. Table 2 showed that there was an indicator with a loading factor below 0.70. They were indicators IP1 and VB1. These indicators were then taken out, resulting all the variable’s loading factor were higher than 0.70. The final result of the factor loading was shown in the Table 3.

**Table 2. Initial Result of Validity Testing Using Convergent Validity**

|         | RDTA  | IB    | IB*IP | IP    | RB    | RB*IP | UB    | UB*IP | VB    | VB*IP |
|---------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| RDTA1   | 0.880 |       |       |       |       |       |       |       |       |       |
| RDTA2   | 0.853 |       |       |       |       |       |       |       |       |       |
| RDTA3   | 0.889 |       |       |       |       |       |       |       |       |       |
| IB * IP |       |       | 1.246 |       |       |       |       |       |       |       |
| IB1     |       | 0.926 |       |       |       |       |       |       |       |       |
| IB2     |       | 0.829 |       |       |       |       |       |       |       |       |
| IP1     |       |       |       | 0.572 |       |       |       |       |       |       |
| IP2     |       |       |       | 0.842 |       |       |       |       |       |       |
| IP3     |       |       |       | 0.711 |       |       |       |       |       |       |
| IP4     |       |       |       | 0.852 |       |       |       |       |       |       |
| RB * IP |       |       |       |       |       | 1.282 |       |       |       |       |
| RB1     |       |       |       |       | 0.778 |       |       |       |       |       |
| RB2     |       |       |       |       | 0.738 |       |       |       |       |       |
| RB3     |       |       |       |       | 0.835 |       |       |       |       |       |
| RB4     |       |       |       |       | 0.860 |       |       |       |       |       |
| UB * IP |       |       |       |       |       |       |       | 1.321 |       |       |
| UB1     |       |       |       |       |       |       | 0.900 |       |       |       |
| UB2     |       |       |       |       |       |       | 0.929 |       |       |       |
| UB3     |       |       |       |       |       |       | 0.853 |       |       |       |
| VB * IP |       |       |       |       |       |       |       |       |       | 1.496 |
| VB1     |       |       |       |       |       |       |       |       | 0.404 |       |
| VB2     |       |       |       |       |       |       |       |       | 0.909 |       |
| VB3     |       |       |       |       |       |       |       |       | 0.895 |       |

**Table 3. Final Result of Validity Testing Using Convergent Validity**

|         | RDTA  | IB    | IB*IP | IP    | RB    | RB*IP | UB    | UB*IP | VB    | VB*IP |
|---------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| RDTA1   | 0.881 |       |       |       |       |       |       |       |       |       |
| RDTA2   | 0.851 |       |       |       |       |       |       |       |       |       |
| RDTA3   | 0.890 |       |       |       |       |       |       |       |       |       |
| IB * IP |       |       | 1.225 |       |       |       |       |       |       |       |
| IB1     |       | 0.925 |       |       |       |       |       |       |       |       |
| IB2     |       | 0.829 |       |       |       |       |       |       |       |       |
| IP2     |       |       |       | 0.844 |       |       |       |       |       |       |
| IP3     |       |       |       | 0.717 |       |       |       |       |       |       |
| IP4     |       |       |       | 0.871 |       |       |       |       |       |       |
| RB * IP |       |       |       |       |       | 1.247 |       |       |       |       |
| RB1     |       |       |       |       | 0.778 |       |       |       |       |       |
| RB2     |       |       |       |       | 0.739 |       |       |       |       |       |
| RB3     |       |       |       |       | 0.835 |       |       |       |       |       |
| RB4     |       |       |       |       | 0.860 |       |       |       |       |       |
| UB * IP |       |       |       |       |       |       |       | 1.299 |       |       |
| UB1     |       |       |       |       |       |       | 0.900 |       |       |       |
| UB2     |       |       |       |       |       |       | 0.929 |       |       |       |
| UB3     |       |       |       |       |       |       | 0.853 |       |       |       |
| VB * IP |       |       |       |       |       |       |       |       |       | 1.472 |
| VB2     |       |       |       |       |       |       |       |       | 0.918 |       |
| VB3     |       |       |       |       |       |       |       |       | 0.915 |       |

Discriminated validity was conducted to strengthen the validity of the construct. The result in table 4 showed that loading value of each indicator for its construct was higher than its cross-loading value, confirming these constructs were valid.

**Table 4. The Result of Cross Loading Estimation Using PLS 3.0**

|         | RDTA         | IB           | IB*IP  | IP           | RB           | RB*IP  | UB           | UB*IP  | VB           | VB*IP  |
|---------|--------------|--------------|--------|--------------|--------------|--------|--------------|--------|--------------|--------|
| RDTA1   | <b>0.881</b> | 0.189        | -0.234 | 0.469        | 0.424        | -0.143 | 0.217        | -0.038 | 0.565        | -0.280 |
| RDTA2   | <b>0.851</b> | 0.085        | -0.047 | 0.456        | 0.210        | -0.187 | 0.477        | -0.051 | 0.530        | -0.150 |
| RDTA3   | <b>0.890</b> | 0.225        | -0.116 | 0.431        | 0.388        | -0.139 | 0.359        | -0.038 | 0.503        | -0.210 |
| IB * IP | -0.154       | 0.129        | 1.000  | -0.228       | -0.018       | 0.556  | 0.032        | 0.152  | -0.167       | 0.403  |
| IB1     | 0.195        | <b>0.925</b> | 0.114  | 0.358        | 0.270        | -0.046 | 0.077        | 0.034  | 0.137        | -0.146 |
| IB2     | 0.132        | <b>0.829</b> | 0.116  | 0.244        | 0.422        | 0.029  | -0.068       | 0.015  | 0.103        | -0.090 |
| IP2     | 0.475        | 0.304        | -0.246 | <b>0.844</b> | 0.286        | -0.124 | 0.125        | 0.059  | 0.309        | -0.136 |
| IP3     | 0.242        | 0.346        | -0.056 | <b>0.717</b> | 0.169        | 0.141  | 0.194        | -0.118 | 0.176        | -0.045 |
| IP4     | 0.479        | 0.252        | -0.199 | <b>0.871</b> | 0.266        | -0.008 | 0.264        | -0.002 | 0.357        | -0.130 |
| RB * IP | -0.179       | -0.018       | 0.556  | -0.028       | 0.030        | 1.000  | -0.069       | 0.161  | -0.127       | 0.469  |
| RB1     | 0.291        | 0.330        | -0.067 | 0.242        | <b>0.778</b> | -0.056 | -0.025       | -0.031 | 0.111        | -0.095 |
| RB2     | 0.222        | 0.339        | -0.054 | 0.173        | <b>0.739</b> | 0.015  | 0.005        | 0.051  | 0.277        | 0.018  |
| RB3     | 0.277        | 0.359        | 0.058  | 0.306        | <b>0.835</b> | 0.119  | -0.005       | -0.107 | 0.219        | -0.111 |
| RB4     | 0.416        | 0.230        | -0.005 | 0.256        | <b>0.860</b> | 0.024  | -0.041       | -0.089 | 0.257        | -0.123 |
| UB * IP | -0.048       | 0.030        | 0.152  | -0.002       | -0.066       | 0.161  | -0.064       | 1.000  | -0.072       | 0.690  |
| UB1     | 0.383        | 0.052        | -0.041 | 0.236        | -0.018       | -0.076 | <b>0.900</b> | -0.054 | 0.583        | -0.110 |
| UB2     | 0.363        | -0.042       | 0.048  | 0.195        | -0.015       | -0.067 | <b>0.929</b> | -0.047 | 0.529        | -0.040 |
| UB3     | 0.318        | 0.047        | 0.088  | 0.196        | -0.037       | -0.037 | <b>0.853</b> | -0.072 | 0.431        | -0.013 |
| VB * IP | -0.246       | -0.139       | 0.403  | -0.139       | -0.108       | 0.469  | -0.064       | 0.690  | -0.169       | 1.000  |
| VB2     | 0.565        | 0.070        | -0.137 | 0.351        | 0.163        | -0.062 | 0.606        | -0.089 | <b>0.918</b> | -0.176 |
| VB3     | 0.554        | 0.185        | -0.170 | 0.315        | 0.328        | -0.172 | 0.455        | -0.043 | <b>0.915</b> | -0.134 |

**Reliability Test**

Reliability testing was used to prove the accuracy and consistency of an instrument to measure construct. The reliability of a construct can be measured by using Cronbach's Alpha (CA) and Composite Reliability (CR). A data is reliable if the CA and/or the CR is higher than 0.7 (Ghozali & Latan, 2015:75). From the data processed, it is found that the CA and CR of each indicator is > 0.7, as shown in Table 5. Therefore, this data was reliable.

**Table 5. The Result of Cronbach's Alpha and Composite Reliability**

| Item  | Cronbach's Alpha (CA) | Composite Reliability (CR) |
|-------|-----------------------|----------------------------|
| UB    | 0.875                 | 0.923                      |
| VBs   | 0.809                 | 0.913                      |
| RB    | 0.822                 | 0.879                      |
| IB    | 0.714                 | 0.871                      |
| IP    | 0.754                 | 0.854                      |
| UB*IP | 1.000                 | 1.000                      |
| VB*IP | 1.000                 | 1.000                      |
| RB*IP | 1.000                 | 1.000                      |
| IB*IP | 1.000                 | 1.000                      |
| RDTA  | 0.845                 | 0.907                      |

Source: Data Analyzed with PLS 3.0

**Coefficient of Determinant Analysis**

The structure of the model was tested by employing inner model testing to predict the causal relationship between latent variables. Coefficient of Determinant ( $R^2$ ) and  $R^2$  Adjusted were evaluated as in table 6 below. This table shows that  $R^2$  of the Resistance to Adopt Digital twin model is 0.525. This shows that the variable in this research contributes to the variation of resistance to adopt digital twin as much as 52%. The rest is determined by another variable outside this model.

**Table 6. R Square and R Square Adjusted**

|                                         | R Square | R Square Adjusted |
|-----------------------------------------|----------|-------------------|
| <b>Resistance to Adopt Digital Twin</b> | 0.552    | 0.525             |

**Goodness of Fit Testing**

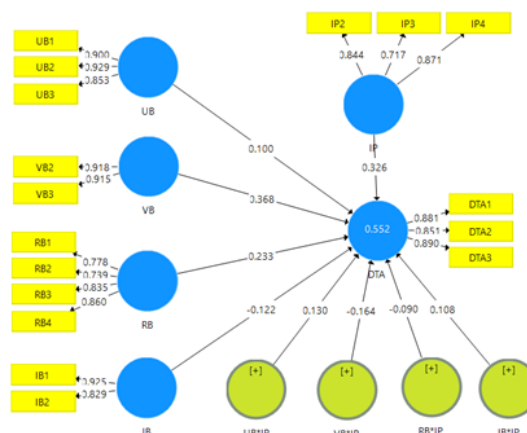
The model fit testing in this research was conducted with two testing model. They were standardized root mean square residual (SRMR) and normal fit index (NFI). According to Hu and Bentler (1998) in Ramayah et al. (2017), model will be considered good fit if the SRMR value is below 1.00. From the data analyzed, it was found that SRMR is 0.077, and it passed the good fit standard. NFI was determined using Chi<sup>2</sup> value (Bentler and Bonett, 1980). Chi<sup>2</sup> was then compared with the benchmark value provided within the Goodness of Fit context. According to Bentler and Bonett (1980) the accepted goodness of fit value when using Chi-square is if the value is higher than 0.9. The analysis found out that NFI is 0.702. Eventhough the NFI value was less than 0,9 it still can be considered marginal fit. Lastly, the RMS theta was 0.192, or close to 0. This is still within the acceptable range. From those three indicators, it can be inferred that the model has met the suitability criteria, can be used and is good at describing the relationship between variables. The model fit testing result is shown in Table 7.

**Table 7. Model Fit**

|                  | Saturated Model | Estimated Model |
|------------------|-----------------|-----------------|
| SRMR             | 0.077           | 0.077           |
| d_ ULS           | 0.915           | 0.899           |
| d_ G             | 0.431           | 0.421           |
| Chi <sup>2</sup> | 424.295         | 411.406         |
| NFI              | 0.702           | 0.711           |
| rms Theta        | 0.192           |                 |

**Individual Testing (Significancy Testing)**

Significancy testing was employed using SmartPLS 3.0 software to test the hypotheses proposed. The path diagram is shown in Figure 2 and 3 below.



**Figure 2. PLS Algo Result**

Source: Data analyzed with SmartPLS 3.0 Software

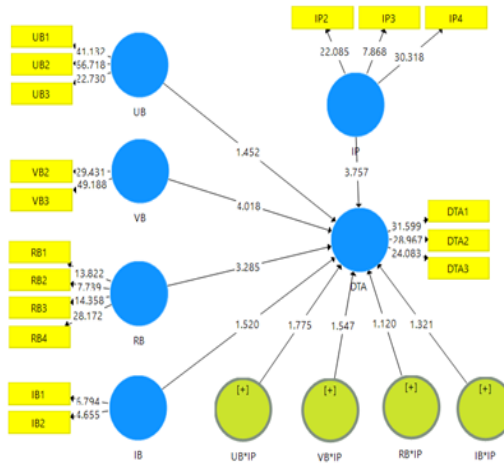


Figure 3. Bootstrapping Result

Source: Data analyzed with SmartPLS 3.0 Software

Descriptive statistical analysis was conducted to understand the information more comprehensively. In this research, mean shows the respondent assessment towards the variable studied, while standard deviation shows the variation of the respondent answer. If the standard deviation is close to zero, the respondent answer is less varied. In contrary, if the standard deviation is far from zero, the answer is more varied. Table 8 shows the statistical descriptive of all indicators.

Table 8. Summary of Statistical Descriptive of All Indicator

| Variables                              | N   | Min  | Max  | Mean | Std. Deviation |
|----------------------------------------|-----|------|------|------|----------------|
| Usage Barrier                          | 161 | 1.00 | 5.00 | 3.47 | 1.05           |
| Value Barrier                          | 161 | 1.00 | 5.00 | 3.96 | 0.89           |
| Risk Barrier                           | 161 | 1.00 | 5.00 | 3.30 | 1.06           |
| Image Barrier                          | 161 | 1.00 | 5.00 | 3.05 | 1.09           |
| Incentive Policy                       | 161 | 1.00 | 5.00 | 3.58 | 1.04           |
| Resistance to Adoption of Digital Twin | 161 | 1.00 | 5.00 | 3.83 | 0.95           |

Coefficient of Determinant

Coefficients of Determination ( $R^2$  adjusted) of the variable was 0.525. This indicates the ability of the independent variable to describe the characteristics or variation of the resistance to adopt digital twin is 52.5%. The remaining factor was described by other independent variables outside this model.

Table 9 The Result of Hypothesis Testing

|             | Hypothesis                                                                                          | The ory | Beta | STD EV | T Stat | P Values | Result                      |
|-------------|-----------------------------------------------------------------------------------------------------|---------|------|--------|--------|----------|-----------------------------|
| UB -> RDT A | H1a: Usage barrier is positively influencing the resistance to adoption of digital twin in industry | +       | 0.1  | 0.069  | 1.452  | 0.073    | H1a Accepted Weak Influence |

|                                       |                                                                                                                                                                |   |           |       |       |       |                                       |
|---------------------------------------|----------------------------------------------------------------------------------------------------------------------------------------------------------------|---|-----------|-------|-------|-------|---------------------------------------|
| <b>VB -&gt;<br/>RDT<br/>A</b>         | <b>H1b:</b> Value barrier is positively influencing the resistance to adoption of digital twin in industry                                                     | + | 0.36<br>8 | 0.092 | 4.018 | 0,000 | H1b Accepted,<br>Strong<br>Influence  |
| <b>RB -&gt;<br/>RDT<br/>A</b>         | <b>H1c:</b> Risk barrier is positively influencing the resistance to adoption of digital twin in industry                                                      | + | 0.23<br>3 | 0.071 | 3.285 | 0.001 | H1c Accepted<br>Strong<br>Influence   |
| <b>IB -&gt;<br/>RDT<br/>A</b>         | <b>H2:</b> Image barriers is positively influencing the resistance to adoption of digital twin in industry                                                     | + | -0.12     | 0.08  | 1.52  | 0.064 | H2 Rejected<br>Weak Influence         |
| <b>IP -&gt;<br/>RDT<br/>A</b>         |                                                                                                                                                                |   | 0.32<br>6 | 0.087 | 3.757 | 0     | -                                     |
| <b>UB*I<br/>P -&gt;<br/>RDT<br/>A</b> | <b>H3a:</b> The relationship between usage barrier and the resistance to adoption of digital twin in industry will be positively moderated by incentive policy | + | 0.13      | 0.073 | 1.775 | 0.038 | H3a Accepted<br>Significant<br>Effect |
| <b>VB*I<br/>P -&gt;<br/>RDT<br/>A</b> | <b>H3b:</b> The relationship between value barrier and the resistance to adoption of Digital Twin in industry will be positively moderated by incentive policy | + | -0.16     | 0.106 | 1.547 | 0.061 | H3b Rejected<br>Not Significant       |
| <b>RB*I<br/>P -&gt;<br/>RDT<br/>A</b> | <b>H3c:</b> The relationship between risk barrier and the resistance to adoption of Digital Twin in industry will be positively moderated by incentive policy  | + | -0.09     | 0.081 | 1.12  | 0.131 | H3c Rejected<br>Not Significant       |
| <b>IB*IP<br/>-&gt;<br/>RDT<br/>A</b>  | <b>H4:</b> The relationship between image barrier and the resistance to adoption of Digital Twin in industry will be positively moderated by incentive policy  | + | 0.10<br>8 | 0.082 | 1.321 | 0.093 | H4 Accepted<br>Not Significant        |

**H1a-c. The relationship between functional barrier and the resistance to adopt digital twin**

From the Tabel 9 above, it was found that the perception of resistance to adoption of digital twin in the industry will increase if the perception of usage barrier, value barrier and risk barrier increase, Therefore H<sub>1a</sub>, H<sub>1b</sub> and H<sub>1c</sub> were accepted. Value barrier and risk barrier has strong influence on the resistance to adopt digital twin (p-value < 0.05). However, the strongest influence on resistance to adopting digital twin is value barrier. This relates to the high investment required in adopting technology in a company.

Hafeez et.al., (2024) mentioned that several challenges in adopting digital twin in industry are high investment cost, the quality of data, the security of data, and the standardization of the model. High investment is required in IT and connectivity infrastructure, together with the additional hurdles of the absence of standardization framework for data collection and model development (Hafeez et al., 2024). Techonology company that offer digital twin technology must address this perception by clearly communicating the anticipated benefits and cost savings associated with the technology to enhance its adoption prospects.

**H2. The relationship between psychological barriers and the resistance to adopt digital twin**

For image barrier, it was found that the coefficient (Beta) was -0.122 (negative). This was not in accordance with the proposed hypotheses in which the image barrier is positively influencing the resistance to adoption of digital twin in industry. Hence, significancy test wa

not conducted and the H<sub>2</sub> was rejected. It is statistically concluded at a 90% confidence level that the image barrier is not influencing the resistance to adoption of digital twin in industry.

**H3a-c. The relationship between functional barrier and the resistance to adopt digital twin will be positively moderated by incentive policy**

From the table above, it was found that the coefficient (Beta) of usage barrier is 0.130 (positive). This indicates that incentive policy has a positive moderating impact on the relationship of the usage barrier and the resistance to adoption of digital twin. If the perception of the usage barrier that is moderated by incentive policy is increasing, the resistance to adopt the digital twin will also increase. This was in accordance with the proposed hypotheses with the P-value of  $0.038 < 0.05$  (Alpha 5%). Therefore, H3a was accepted with **significant** effect and confirmed the research conducted by Jaiswal et al. (2021) stating that incentive policy has positive moderating effect for technology adoption (Jaiswal et al., 2021).

For value barrier, it was found that the coefficient (Beta) of value barrier was -0.164 (negative). If the perception of the value barrier that is moderated by incentive policy is increasing, the resistance to adopt the digital twin will decrease. This result was not in accordance with the proposed hypothesis where value barrier will be positively moderated by incentive policy. Hence, H3b was rejected and a significance test was not conducted.

For risk barrier, it was found that the coefficient (Beta) is -0.090 (negative). This indicates, if the perception of the risk barrier that is moderated by incentive policy is increasing, the resistance to adopt the digital twin will decrease. This result was not in accordance with the proposed hypothesis where value barrier will be positively moderated by incentive policy. Hence, H3c was rejected and a significance test was not conducted. For value and risk barrier, it was concluded that incentive policy was not able to positively moderating the value and risk barrier to handle the resistance to adopt the digital twin. This is probably due to the inadequacy of policy incentives that meets the consumer needs.

**H4. The relationship between psychological barrier and the resistance to adoption of digital twin in industry will be positively moderated by incentive policy.**

From the table above, it was found that the coefficient (Beta) of image barrier that is moderated by incentive policy was 0.108 (positive). This indicates that incentive policy has a positive moderating impact on the relationship of the image barrier and the resistance to adoption of digital twin. If the perception of the image barrier that is moderated by incentive policy is increasing, the resistance to adopt the digital twin will also increase. This was in accordance with the proposed hypotheses with the P-value of 0.093 or more than 0.05. Therefore, H4 was accepted, and it was statistically concluded at a 95% confidence level that the incentive policy positively moderates the relationship of image barrier to the resistance adoption of digital twin in industry, however the effect is not significant.

**CONCLUSION**

From his research, it can be concluded that usage barrier, value barrier, and risk barrier are positively influencing the resistance to adopt digital twin in industry, while image barrier is negatively influencing the resistance to adopt digital twin in industry. The primary barrier to the resistance of adopting digital twin in Indonesia is value barrier. Incentive policy has moderating influence on the relationship between barrier and the resistance to adopting digital twin. For usage barrier and image barrier, it is positive moderating influence. However, for value barrier and risk barrier, it is negative moderating influence.

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