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Orginal Article

AI Readiness, Perceptions, and Resilience Impact on Supply Chain Performance in Tangerang

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Abstract

This study aims to analyze the influence of AI Readiness, Perceived Usefulness, Perceived Ease of Use, Behavioral Intention, and Supply Chain Visibility on Supply Chain Performance, with Supply Chain Resilience as a mediating variable. The research was conducted among employees of companies involved in the supply chain in the Tangerang area. The study uses a quantitative approach with Partial Least Squares Structural Equation Modeling (PLS-SEM) analysis. The results show that AI Readiness, Perceived Ease of Use, and Supply Chain Visibility have a significant effect on Supply Chain Performance. In addition, Supply Chain Visibility also significantly influences Supply Chain Resilience, which in turn contributes to Supply Chain Performance. On the other hand, Perceived Usefulness and Behavioral Intention do not have a significant impact on Supply Chain Performance. These findings highlight the importance of technology readiness, supply chain visibility, and supply chain resilience in supporting operational performance and competitive advantage in the modern era. The study also provides strategic insights for companies to invest in artificial intelligence-based technologies and strengthen supply chain integration.
Keywords: AI Readiness, Perceived Usefulness, Perceived Ease of Use, Behavioral Intention, Supply Chain Visibility, Supply Chain Resilience, Supply Chain Performance

1. Introduction

The advancement of technology in the era of Industry 4.0 has brought about significant changes across various sectors, including manufacturing and distribution. The adoption of modern technologies, such as Artificial Intelligence (AI), has become a key driver in enhancing operational efficiency and maintaining competitiveness in an increasingly globalized market. Within supply chains, AI not only improves the speed and accuracy of decision-making but also strengthens a company's adaptability to market dynamics. Research into the implementation of AI in supply chains has become crucial due to its substantial contribution to operational efficiency, responsiveness, and sustainability.

Despite its potential, the implementation of AI in Indonesia presents unique challenges. The Indonesian government, through initiatives like the "Making Indonesia 4.0" program, has actively encouraged industrial digitalization. However, the readiness for technological adoption across industries remains uneven. Prior studies, such as Suhari (2013), have highlighted the importance of technology readiness and supply chain visibility in improving supply chain effectiveness. Similarly, Saputra (2019) emphasized that robust supply chain visibility enhances resilience, enabling companies to mitigate disruptions effectively. While these studies have provided valuable insights, they often focus on technical or infrastructural factors, primarily within large, established corporations.

In Tangerang, a thriving industrial hub in Indonesia, the challenges of AI adoption are compounded by specific local factors. Tangerang is home to a diverse range of businesses,

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including manufacturing, logistics, and distribution companies, many of which operate with varying levels of technological sophistication. For smaller and mid-sized enterprises, limitations in human resources, inadequate technological infrastructure, and skepticism regarding the perceived benefits of AI adoption present significant barriers. Companies often struggle to balance the costs of AI implementation with its potential benefits, leading to hesitation in adopting advanced technologies. Additionally, a lack of localized frameworks for integrating AI into supply chain operations exacerbates these issues, making it harder for businesses to build the resilience needed to withstand disruptions.

AI readiness, which encompasses organizational preparedness, employee mindset, and infrastructural capabilities, is a critical determinant of successful AI implementation. Previous research has examined the role of AI readiness in improving supply chain performance, but its relationship with supply chain resilience remains underexplored, particularly in Indonesia. Supply chain resilience is increasingly recognized as a crucial factor in maintaining operational stability and performance amidst disruptions. For Tangerang-based companies, understanding how AI readiness influences resilience, and in turn, impacts supply chain performance, is essential to navigating the challenges of a dynamic industrial landscape.

This study aims to fill this gap by exploring the relationships between AI readiness, perceived usefulness, perceived ease of use, behavioral intention, and supply chain visibility, with supply chain resilience serving as a mediating variable. Focusing on companies involved in supply chains in Tangerang, this research provides a localized perspective on the challenges and opportunities associated with AI adoption. By examining the interplay between these variables, the study offers strategic insights into how companies in Tangerang can leverage AI technologies to enhance their supply chain performance and build resilience in the face of an increasingly uncertain global market.

2. Method

This study employs a quantitative approach with a survey method to analyze the relationships between AI readiness, perceived usefulness, perceived ease of use, behavioral intention, and supply chain visibility on supply chain performance, with supply chain resilience as a mediating variable. A quantitative approach was chosen because it allows for the systematic and standardized measurement of variables, enabling statistical testing of relationships.

The study population consists of employees involved in supply chain processes in the Tangerang area, including logistics managers, operational staff, and supply chain analysts. This study uses a non-probability sampling method with a convenience sampling technique, allowing for the selection of respondents based on ease of access. Respondents were selected based on the following criteria: they work in supply chain-related roles, have been employed at their company for at least six months, and are located in Tangerang. While this method may introduce bias due to its less representative nature, it was chosen due to time constraints and accessibility limitations. To mitigate bias, a large sample size (200 respondents) was employed, and diversity in job roles and company types was ensured to improve the validity of the findings.

Data collection was conducted via an online questionnaire using Google Forms, offering respondents the flexibility to complete the survey at any time, thereby increasing participation rates. Before the main survey, the questionnaire was pilot-tested with 30

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respondents who met the study's criteria. The pilot test aimed to evaluate the clarity, relevance, and reliability of the questionnaire items. Feedback from pilot respondents was used to refine the wording of questions and improve the overall questionnaire design. At this stage, internal reliability was tested using Cronbach's Alpha, and all constructs demonstrated satisfactory reliability ($\alpha > 0.70$). Construct validity was assessed using item-total correlation and exploratory factor analysis to ensure that each item appropriately measured the intended variable.

The collected data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). This method was chosen over traditional SEM approaches or ordinary regression for several reasons. First, PLS-SEM is more flexible with small sample sizes and does not require a large sample to yield reliable results. Second, this method can handle complex models, including those with multiple latent variables and mediation effects, as used in this study. Third, PLS-SEM emphasizes predictive accuracy, which aligns with the study's objective of exploring the practical implications of AI readiness and supply chain resilience. Additionally, PLS-SEM effectively handles multicollinearity between indicators, ensuring more stable relationships among variables.

The analysis was conducted in two stages. The first stage involved an outer model analysis to test the validity and reliability of the constructs. Convergent validity was assessed through loading factor values and Average Variance Extracted (AVE), while discriminant validity was evaluated using cross-loadings and the Heterotrait-Monotrait (HTMT) ratio. Reliability was tested using Composite Reliability (CR) and Cronbach's Alpha. The second stage involved an inner model analysis to evaluate the relationships between latent variables. This included multicollinearity testing, coefficients of determination (R^2), predictive relevance (Q^2), and hypothesis testing using bootstrapping. By employing PLS-SEM, this study provides in-depth insights into the relationships between AI readiness, supply chain visibility, and resilience, as well as their collective impact on supply chain performance.

3. Results and Discussion

Data Description

The data collection in this study was conducted with 200 respondents, all employees working in supply chain companies in the Tangerang area using convenience sampling. Respondents were selected based on ease of access and the following criteria: they are employees working in the supply chain field, have at least six months of experience, and come from various companies in the Tangerang area.

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Table 1
Description of Research Data

Category	Frequency	Percentage
	Age	
21-25 Years	21	10,50%
26-30 Years	140	70,00%
31-35 Years	23	11,50%
36-40 Years	8	4,00%
41-45 Years	6	3,00%
46-50 Years	2	1,00%
	Gender	
Male	108	54,00%
Female	92	46,00%
	Years of Work Experience	
6 Month - 1 Years	18	9,00%
1 - 4 Years	139	69,50%
> 5 Years	43	21,50%

Based on Table 1, the majority of respondents are aged between 26 and 30 years, which represents a highly productive and adaptable age group. This demographic is generally more open to adopting new technologies, including AI, due to their exposure to digital tools and innovations in their professional and personal lives. Their willingness to embrace change and technological advancements can play a pivotal role in accelerating the transformation of supply chains. While the majority of respondents are male, a significant proportion are female, highlighting the increasing involvement of women in supply chain management. This diversity in the workforce can bring varied perspectives, enhance problem-solving capabilities, and foster more inclusive approaches to the adoption of new technologies.

Regarding work experience, most respondents have 1–4 years of experience, indicating a developing yet solid understanding of supply chain dynamics. This group is typically at a stage where they are open to learning and integrating new methods into their workflows. Respondents with over five years of experience offer valuable insights into the long-term benefits and challenges of implementing AI in supply chains, as their tenure allows them to draw on extensive practical knowledge. Meanwhile, those with less than one year of experience are in the early stages of their careers but are poised to contribute to the future of supply chain innovation. Exposing this group to AI technologies early on can foster a generation of professionals who are proficient in utilizing digital tools. The diverse range of experience among respondents provides a comprehensive view of the workforce's readiness for AI adoption and highlights the need for tailored training programs to ensure that all employees, regardless of experience, are equipped to support AI-driven supply chain enhancements.

Descriptive Statistics

Descriptive statistics provide an overview of respondents' assessments of each variable in this study, including average responses and their interpretation. This data helps to understand respondents' perceptions of AI-based technologies, ease of use, perceived benefits, usage intentions, supply chain visibility, supply chain resilience, and supply chain performance.

Table 2

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Descriptive Statistics AI Readiness Variable

ITEM	STATEMENT	MEAN
1	I believe AI technology will have a positive impact on the company	4,64
2	I am confident that our team is ready to adopt AI technology	4,31
3	I am open to trying new AI-based solutions	4,37
4	My company encourages innovation in the use of technology	4,43
5	I find it difficult to adapt to AI-based systems	4,93
6	I feel uncomfortable with the changes brought by AI technology	4,65
7	I feel uncertain about my ability to use AI technology	4,56
8	I worry about losing my job due to AI adoption	4,74

Based on Table 2, the average values for the AI Readiness variable show that respondents generally have a high level of readiness to adopt AI-based technology. Most of the items received average values above 4.5, indicating a strong agreement with the positive impact of AI technology and the organization's readiness to innovate.

Table 3
Descriptive Statistics Perceived of Usefulness *Variable*

ITEM	STATEMENT	MEAN
9	The use of AI systems improves my individual performance	4,52
10	I find that AI systems help me in my daily tasks	4,46
11	The use of AI systems increases my productivity	4,19
12	I feel more productive when using AI systems	4,22
13	AI systems improve performance effectiveness	4,27
14	I feel more efficient due to the use of AI systems	4,31
15	The use of AI systems is beneficial to me	4,49
16	I feel that AI systems add value to my work	4,33

Table 3 shows that respondents generally perceive AI as highly beneficial to their productivity. The majority of respondents strongly agree that AI helps improve individual performance, indicating that they clearly recognize the positive impact of AI technology.

Table 4
Descriptive Statistics Perceived Ease of Use Variable

ITEM	STATEMENT	MEAN
17	My interaction with the AI system is clear and easy to understand	4,23
18	I do not find it difficult to interact with the AI system	4,09
19	I do not need much effort to interact with the AI system	3,98
20	I find the AI system intuitive to use	4,16
21	AI systems are easy to use	4,27
22	I can operate the AI system as needed without difficulty	4,10
23	I can use the AI system smoothly	4,28
24	Operating the AI system as I want is very easy	4,14

Table 4 shows that respondents generally find AI systems easy to use, as most items fall under the "Agree" and "Strongly Agree" categories. However, some respondents still reported slight difficulty in fully utilizing the system, indicating areas for further improvement in user-friendliness.

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Table 5
Descriptive Statistics Behavioral Intention *Variable*

ITEM	STATEMENT	MEAN
25	I intend to use AI systems in the future	4,62
26	I plan to continue using AI systems	4,37
27	I want to frequently use AI systems in my work	4,32
28	I am interested in integrating AI systems into my daily activities	4,11
29	I want to use AI systems in my daily life	4,15
30	I find AI systems very relevant to my daily routine	4,09
31	I am willing to use AI systems regularly	4,36
32	I feel it is important to use AI systems in my daily activities	4,12

Table 5 shows a strong intention among respondents to continue using AI systems in the future. Most respondents rated their willingness to integrate AI into their daily activities positively, with average scores near the "Strongly Agree" category.

Table 6
Descriptive Statistics Supply Chain Visibility Variable

ITEM	STATEMENT	MEAN
33	AI systems provide information before changes in demand occur	4,35
34	I can obtain the necessary information before changes occur	4,30
35	AI systems allow knowledge sharing about core business processes	4,26
36	We share information about business processes through AI systems	4,29
37	We share information about customer needs	4,36
38	AI systems support collaboration in understanding customer needs	4,42
39	AI systems enhance the integration of activities across the supply chain	4,32
40	I feel more integrated using AI systems	4,29
41	AI systems support collaboration to monitor product movements	4,36
42	We collaborate better due to AI systems	4,33

Table 6 shows that respondents have a very high perception of AI’s role in supporting collaboration, integration, and visibility across the supply chain. This indicates that AI significantly contributes to enhancing coordination and efficiency across various processes.

Table 7
Descriptive Statistics Supply Chain Resilience Variable

ITEM	STATEMENT	MEAN
43	I can re-engineer processes to enhance resilience	4,17
44	Business processes can be quickly adjusted when changes occur	4,26
45	I am able to adapt to market changes	4,24
46	AI systems support me in being more responsive	4,46
47	Team collaboration supports supply chain resilience	4,15
48	I work well with others to enhance resilience	4,10
49	The risk management culture in the supply chain is well established	4,14
50	increases resilience to future disruptions	4,11

Table 7 shows that AI plays a key role in enhancing resilience in the supply chain by supporting quick response to disruptions and market changes. It helps teams collaborate and re-engineer processes for greater flexibility.

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Table 8
Descriptive Statistics Kinerja Rantai Pasokan *Variable*

ITEM	STATEMENT	MEAN
51	My supply chain is reliable	4,35
52	he products I deliver are always on time	4,42
53	I am responsive to customer demands	4,41
54	I can quickly adapt to changes in customer needs	4,27
55	I am able to control costs within the supply chain	3,97
56	Operational costs are more efficient thanks to the use of AI systems	4,14
57	I can optimize asset utilization in the supply chain	4,08
58	I have good asset management to support performance	4,17

Based on Table 8, the Supply Chain Performance variable demonstrates positive outcomes, particularly in key areas such as reliability, on-time delivery, and responsiveness to customer needs. These strengths highlight the effectiveness of current supply chain practices in meeting customer expectations and ensuring timely product availability. Reliability and responsiveness are critical factors that contribute to maintaining customer trust and competitive advantage, reflecting the potential of AI technologies to further enhance these aspects through better forecasting, real-time tracking, and decision-making capabilities. However, the results also reveal areas of concern, particularly in cost management and operational efficiency, where performance is comparatively weaker. High operational costs and suboptimal resource utilization indicate the need for more robust strategies to control expenses and streamline processes. By integrating AI solutions for predictive analytics, process optimization, and inventory management, companies could address these challenges more effectively. Furthermore, targeted investments in training employees and upgrading infrastructure may help mitigate inefficiencies and drive cost savings, ensuring a more balanced and sustainable improvement in overall supply chain performance. These findings underscore the importance of not only leveraging technology for immediate gains but also fostering a long-term strategic approach to tackling cost-related inefficiencies in the supply chain.

Structural Equation Modeling (SEM)

Structural Equation Modeling (SEM) was used in this study to examine the relationships between the variables studied: AI Readiness, Perceived Usefulness, Perceived Ease of Use, Behavioral Intention, Supply Chain Visibility, Supply Chain Resilience, and Supply Chain Performance. SEM allows researchers to test theoretical models developed based on research hypotheses.

Measurement Model Analysis (Outer Model)

The outer model ensures that the relationships between the indicators and latent variables are valid and reliable. Evaluation was carried out through convergent validity (loading factor and Average Variance Extracted/AVE) as well as discriminant validity (cross-loading and Heterotrait-Monotrait Ratio/HTMT). Reliability was assessed using Composite Reliability and Cronbach’s Alpha. The analysis results showed that the research model was valid and reliable, with certain indicators retained based on theoretical relevance.

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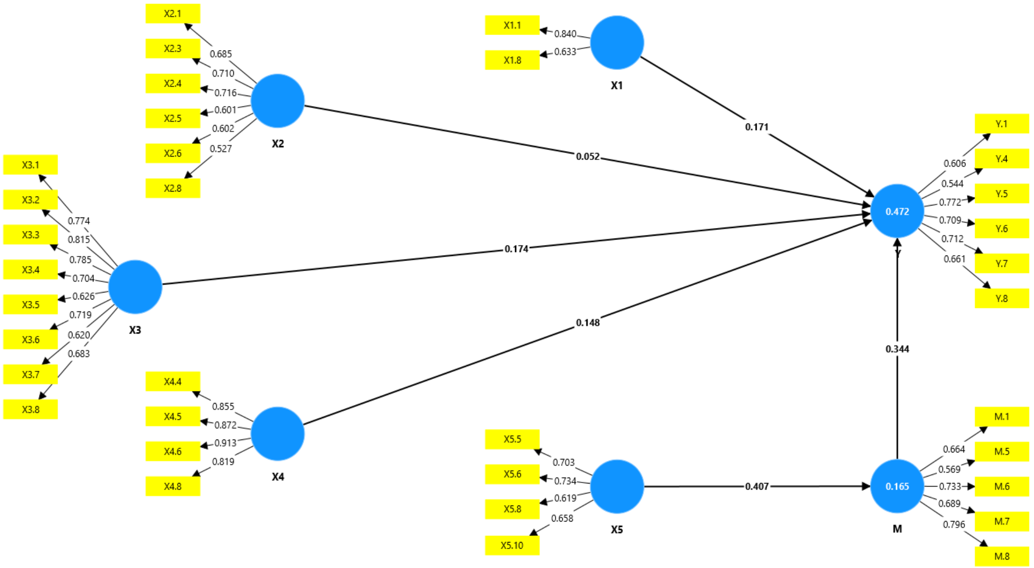
Figure 1
SEM-PLS Model



Based on Figure 1, the initial model included all indicators, including those with loading factors below 0.70. The model was then refined by removing indicators with a loading factor below 0.50. The final model (Figure 1) retained indicators that were valid and theoretically significant, with improved validity and reliability.

Table 9.
Loading Factor

Indikator	X1	X2	X3	X4	X5	M	Y
Tertinggi	0,84	0,716	0,815	0,913	0,734	0,796	0,772
Terendah	0,633	0,527	0,62	0,819	0,619	0,569	0,544

The evaluation of the outer model showed that most indicators had loading factors above 0.70, indicating that these indicators contributed well to the constructs being measured. However, some indicators with loading factors between 0.50 and 0.70 were retained because they had important theoretical relevance. For example, the indicator with the highest loading factor was X4 (Behavioral Intention) with a loading factor of 0.913, while the indicator with the lowest loading factor was X2 (Perceived Usefulness) with a loading factor of 0.527.

Table 10
Average Variance Extracted

Indicator	AVE
X1 (AI Readiness)	0,553
X2 (Perceived Usefulness)	0,414
X3 (Perceived Ease of Use)	0,517
X4 (Behavioral Intention)	0,749
X5 (Supply Chain Visibility)	0,462
M (Supply Chain Resilience)	0,482
Y (Supply Chain Performance)	0,451

Based on Table 10, the Average Variance Extracted (AVE) for most constructs also shows good results, with values above 0.50, indicating sufficient convergent validity.

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However, some constructs with AVE values below 0.50 were still retained due to their theoretical relevance. The construct X2 (Perceived Usefulness) has an AVE value of 0.414, which is slightly below 0.50 but has been retained to maintain theoretical continuity.

Table 11
Heterotrait-Monotrait Ratio Values

HTMT (Heterotrait-Monotrait Ratio)	HTMT
X1 <-> M	1,017
X2 <-> M	0,674
X2 <-> X1	1,276
X3 <-> M	0,633
Y <-> M	0,778

Based on Table 11, the cross-loading results show that each indicator has the highest loading value on its relevant construct, indicating that the indicators correctly represent the constructs they are intended to measure. HTMT analysis reveals several construct pairs that have values above the 0.90 threshold, such as between X1 and M with an HTMT value of 1.017, indicating a strong relationship between these constructs.

Table 12
Composite Reliability Results

Composite Reliability (CR)	CR
X1 (AI Readiness)	0,709
X2 (Perceived Usefulness)	0,808
X3 (Perceived Ease of Use)	0,894
X4 (Behavioral Intention)	0,922
X5 (Supply Chain Visibility)	0,774
M (Supply Chain Resilience)	0,822
Y (Kinerja Rantai Pasokan)	0,83

Based on Table 12, he Composite Reliability (CR) results indicate that most constructs have CR values above 0.70, suggesting good internal consistency. The construct with the highest CR value is X4 (Behavioral Intention) with a value of 0.922, while the construct with the lowest CR value is X1 (AI Readiness) with a value of 0.709. Overall, the evaluation of the Outer Model suggests that the model being constructed has good validity and reliability, though there are some indicators and constructs that require further attention to enhance the quality of the research model.

Structural Model Analysis (Inner Model)

The inner model evaluates the relationships between latent variables based on hypotheses. The analysis includes testing path coefficients, R^2 values, effect sizes (F^2), predictive relevance (Q^2), and multicollinearity through Variance Inflation Factor (VIF). The results provide insights into the strength of relationships and influences between latent variables.

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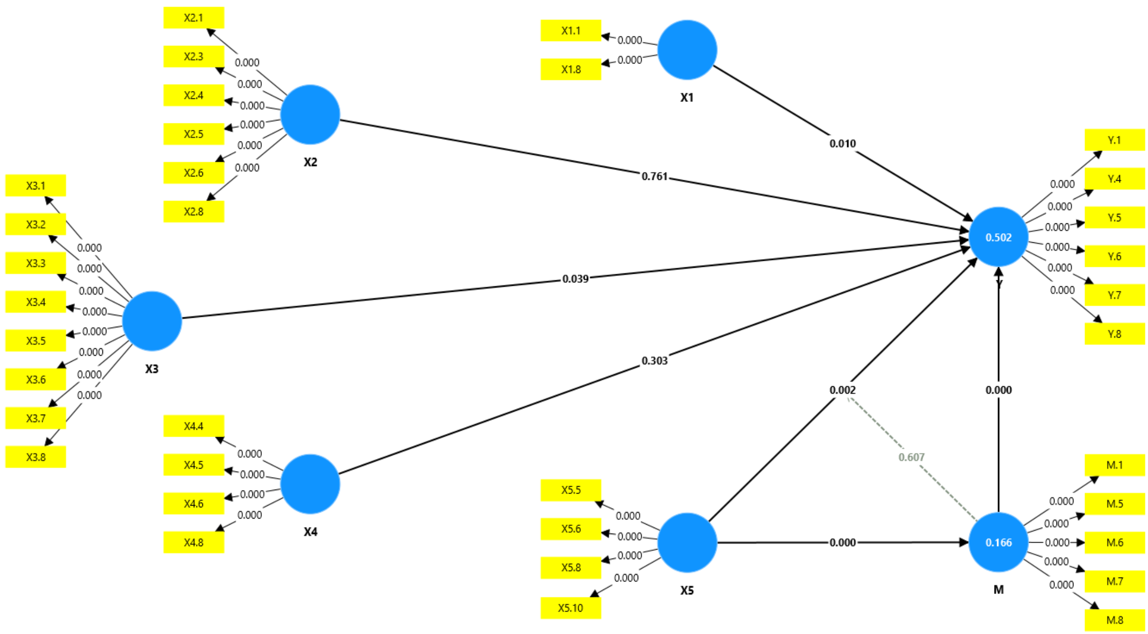
Figure 2
Boostrapping Model



Based on Figure 2, the path coefficient is a key indicator in structural model analysis. It reflects the magnitude of the direct influence of an independent variable on a dependent variable. The following table shows the path coefficients, t-statistics, p-values, and significance levels for the hypothesized relationships in the model.

Table 13
Path Coefficient

	Path Coefficient	T-Statistik	*P-value*	Sig
X_1 (*AI Readiness*) → Y (Kinerja Rantai Pasokan)	0,171	3,086	0,002	Significant
X_2 (*Perceived Usefulness*) → Y (Kinerja Rantai Pasokan)	0,052	0,675	0,501	Tidak Significant
X_3 (*Perceived Ease of Use*) → Y (Kinerja Rantai Pasokan)	0,174	1,771	0,078	Tidak Significant
X_4 (*Behavioral Intention*) → Y (Kinerja Rantai Pasokan)	0,148	1,915	0,057	Mendekati Significant
X_5 (*Supply Chain Visibility*) → M (*Supply Chain Resilience*)	0,407	6,517	0,000	Significant
M (*Supply Chain Resilience*) → Y (Kinerja Rantai Pasokan)	0,344	4,688	0,000	Significant

Based on Table 13, the path coefficient test results reveal that variables AI Readiness, Supply Chain Visibility, and Supply Chain Resilience significantly impact Supply Chain Performance, emphasizing the importance of organizational readiness for technology adoption, process transparency, and adaptability to disruptions. On the other hand, Perceived Usefulness and Perceived Ease of Use do not show a significant influence on Supply Chain Performance, potentially due to other more dominant factors. Additionally, the relationship between Behavioral Intention and Supply Chain Performance is approaching significance, indicating the relevance of behavioral intention but requiring further attention.

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The Coefficient of Determination (R^2) measures the proportion of variation in a dependent variable that is explained by the independent variables in the model. A higher R^2 value indicates a stronger explanatory power of the model. Based on the analysis, the Supply Chain Resilience variable has an R^2 value of 0.165, which is considered low. This implies that the model can only explain 16.5% of the variation in supply chain resilience, leaving a substantial portion unexplained. This low R^2 value suggests that factors not included in the model, such as organizational culture, external disruptions, leadership practices, or industry-specific challenges, may play a significant role in shaping supply chain resilience. For instance, while AI readiness and supply chain visibility are critical, resilience may also depend heavily on risk management strategies, collaboration with partners, and the ability to reconfigure supply chains during crises. These unexplored factors highlight areas for future research to develop a more comprehensive understanding of the determinants of supply chain resilience.

In contrast, the Supply Chain Performance variable has an R^2 value of 0.472, which is categorized as moderate. This indicates that the model explains approximately 47.2% of the variation in supply chain performance, suggesting that the tested variables such as AI readiness, perceived ease of use, and supply chain visibility have a considerable influence. However, the remaining unexplained variance points to the presence of other external factors, such as market dynamics, regulatory frameworks, or competitive pressures, that may also impact performance. While the R^2 value for supply chain performance shows that the model provides a solid foundation for understanding the tested relationships, it also emphasizes the need to consider additional variables or contextual factors in future studies to gain a more nuanced perspective. These findings underscore the importance of refining models and broadening the scope of analysis to better capture the complexity of supply chain resilience and performance.

Effect Size (F^2) is used to assess the contribution of each independent variable to the dependent variable in the structural model. In this study, most of the relationships between variables show very small F^2 values, indicating that their influence on supply chain performance is relatively insignificant. For example, the relationships between AI Readiness and Supply Chain Resilience with Supply Chain Performance show F^2 values close to 0, indicating very weak contributions. However, the relationship between Supply Chain Visibility and Supply Chain Resilience shows a slightly higher F^2 value (0.053), suggesting a small but important effect on supply chain resilience.

Predictive Relevance (Q^2) is a measure used to evaluate the predictive ability of the model in reconstructing observed values based on the estimated parameters. The analysis shows that most exogenous constructs, such as AI Readiness and Perceived Usefulness, do not have significant predictive contributions, with a Q^2 value of 0. This indicates that these variables do not effectively predict endogenous variables, such as performance or resilience. However, the variable Supply Chain Resilience has a Q^2 value of 0.072, which is considered small, while Supply Chain Performance has a Q^2 value of 0.180, indicating a fairly good predictive relevance. This positive Q^2 value supports the notion that, although some exogenous variables do not significantly contribute to predictions, endogenous variables are more effective in explaining the existing variation.

Variance Inflation Factor (VIF) is used to detect multicollinearity between indicators in the model. The analysis shows that all indicators in the model have VIF values below 5, meaning that there is no significant multicollinearity. This is important to ensure that the

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results of the analysis are not distorted by redundancy among the variables being tested. The low VIF values indicate that each indicator can function independently without significant overlap, making the model more stable and reliable for further research.

Hypothesis Testing

Hypothesis testing was conducted to analyze the relationships between latent variables based on the research model. This test was performed using Partial Least Squares Structural Equation Modeling (PLS-SEM), considering the path coefficient, t-value, and p-value.

Table 14
Hypothesis Testing Results

Hypothesis	Path Coefficient	t-value	p-value	Conclusion
H1: AI Readiness has a positive and significant effect on supply chain performance	0.149	2.608	0.01	Significant
H2: Perceived Usefulness has a positive and significant effect on supply chain performance	-0.027	0.305	0.761	Not significant
H3: Perceived Ease of Use has a positive and significant effect on supply chain performance	0.200	2.082	0.039	Significant
H4: Behavioral Intention has a positive and significant effect on supply chain performance	0.083	1.032	0.303	Not significant
H5: Supply Chain Visibility has a positive and significant effect on Supply Chain Resilience	0.408	6.429	0.000	Significant
H6: Supply Chain Resilience has a positive and significant effect on supply chain performance	0.313	4.245	0.000	Significant
H7: Supply Chain Visibility has a positive effect on supply chain performance, mediated by Supply Chain Resilience	-0.024	0.515	0.607	Not significant

Based on Table 14, the hypothesis testing results show that most of the relationships between variables in the research model are significant. Hypotheses H1, H3, H5, and H6 are significant, with p-values below 0.05, indicating that the variables AI Readiness, Perceived Ease of Use, Supply Chain Visibility, and Supply Chain Resilience have a positive and significant effect on the related dependent variables. For example, Supply Chain Visibility has a strong influence on Supply Chain Resilience, while Supply Chain Resilience itself also significantly affects Supply Chain Performance. On the other hand, some hypotheses such as H2, H4, and H7 are not significant, with p-values above 0.05. This indicates that Perceived Usefulness and Behavioral Intention do not have a strong enough impact on Supply Chain Performance in the context of this study. Additionally, the mediating effect of Supply Chain Visibility on Supply Chain Performance through Supply Chain Resilience was also found to be insignificant. These results provide insights that while most variables have significant contributions, some variables may require different approaches to have a more noticeable impact on supply chain performance.

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Discussion

Based on the research findings, the influence of the AI Readiness variable on Supply Chain Performance is found to be significant, supporting the hypothesis that readiness for AI-based technologies plays a crucial role in improving supply chain efficiency. This is consistent with the theory explained by Parasuraman & Colby (2015), where dimensions of optimism and innovation in technology readiness positively influence the adoption of new technologies. In the context of supply chains, AI Readiness enables companies to adopt advanced technologies such as real-time data analytics, which helps optimize inventory and predict customer demand. As a key pillar in modernizing supply chains, an organization's readiness for AI technologies can reduce uncertainty, increase productivity, and ensure sustainable performance.

On the other hand, the Perceived Usefulness variable did not show a significant effect on Supply Chain Performance. This indicates that the mere perception of technology's usefulness is not enough to drive improvements in supply chain performance. According to Davis (1989), the perception of usefulness must be balanced with the perception of ease of use (Perceived Ease of Use) to maximize technology adoption. In this study, the Perceived Ease of Use variable was found to significantly affect Supply Chain Performance, reinforcing the argument that systems that are easy to use instill trust and comfort in users, ultimately contributing to the efficiency of logistics and operational processes. Systems with intuitive interfaces, as explained by Brown (2011), allow users to focus on strategic tasks without being distracted by technological complexities.

The Supply Chain Visibility variable demonstrated a significant positive effect on Supply Chain Resilience, supporting the theory that visibility in the supply chain helps identify risks and accelerates decision-making. According to Kurniawan et al. (2017), visibility allows companies to track product movements in real-time, improve inventory planning, and reduce operational bottlenecks. The Supply Chain Resilience gained from this visibility also had a significant impact on Supply Chain Performance, as discussed by Abeysekara et al. (2019). This resilience ensures that companies can adapt to disruptions without diminishing customer satisfaction or operational efficiency.

However, the effect of Behavioral Intention on Supply Chain Performance was not significant, possibly due to a lack of confidence in the long-term benefits of technology in the context of their organization. According to Ajzen (2020) in the Theory of Planned Behavior, behavioral intention is often influenced by external factors such as the work environment or pressure from others, which may limit technology adoption despite its potential benefits. In this case, organizational intervention is necessary to enhance individual confidence and motivation in using new technologies.

This study reveals that technology readiness, ease of use, and supply chain visibility are the key factors influencing supply chain performance. Although some variables, such as Perceived Usefulness and Behavioral Intention, were not significant, the results provide strategic guidance for companies to focus on strengthening supply chain resilience through the adoption of relevant technologies, providing training to improve user comfort, and investing in advanced visibility systems.

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4. Conclusion

This study shows that AI Readiness has a positive and significant effect on Supply Chain Performance, highlighting the importance of organizational readiness in adopting AI-based technologies. With a high level of readiness, companies can leverage these technologies to improve operational efficiency, manage inventory optimally, and respond to customer demands more effectively. This aligns with the Technology Readiness theory, which emphasizes that optimism and innovation toward technology drive the adoption of new technologies to enhance productivity and operational effectiveness.

Furthermore, Perceived Ease of Use also has a positive impact on Supply Chain Performance, indicating that technologies that are easy to use can build user trust and accelerate work processes. Users who feel comfortable with the technology system are more likely to engage with it effectively, thereby supporting work efficiency and productivity. However, the variables Perceived Usefulness and Behavioral Intention did not show a significant impact in this study. This suggests that the perceived benefits of technology and individuals' intentions to use it are not sufficient to drive performance improvements without additional support, such as simple system design and adequate training.

On the other hand, Supply Chain Visibility has a positive effect on Supply Chain Resilience, which in turn impacts Supply Chain Performance. Good supply chain visibility allows companies to monitor processes in real-time, detect potential disruptions earlier, and plan appropriate mitigation measures. The resilience in the supply chain that stems from this visibility helps companies maintain smooth operations even when facing challenges. Therefore, enhancing visibility and strengthening supply chain resilience become strategic steps necessary to increase a company's competitiveness in an increasingly dynamic market.

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