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The Effect of AI Implementation, Logistics Information System Integration, and WMS on Operational Efficiency and Customer Satisfaction in Indonesian Logistics Companies

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ABSTRACT
The Indonesian logistics industry is undergoing rapid digital transformation through the adoption of artificial intelligence (AI), Logistics Information System (LIS) integration, and Warehouse Management Systems (WMS). However, empirical studies examining the simultaneous effects of these technologies on operational efficiency and customer satisfaction remain limited. This study investigates the influence of AI implementation, LIS integration, and WMS adoption on operational efficiency and customer satisfaction in Indonesian logistics companies. A quantitative explanatory research design was applied using purposive sampling. Data were collected from 350 respondents, including logistics managers, warehouse supervisors, IT managers, and supply chain coordinators across Indonesia. The data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS 4. The results show that AI implementation, LIS integration, and WMS adoption have positive and significant effects on operational efficiency. Operational efficiency also significantly improves customer satisfaction. Among the three digital technologies, AI implementation has the strongest standardized effect, followed by LIS integration and WMS adoption. The findings confirm that operational efficiency plays a crucial role in linking digital technology adoption with customer-related outcomes. This study contributes to TAM, RBV, TOE, and Digital Transformation Theory and provides practical insights for improving logistics performance.

Keywords: Artificial Intelligence, Logistics Information System Integration, Warehouse Management System, Operational Efficiency, Customer Satisfaction.

I. Introduction

The logistics industry in Indonesia has experienced substantial growth over the past decade, driven primarily by rapid e-commerce expansion, increasing digitalization, and the rising demand for faster and more reliable distribution services. According to the World Bank (2025), Indonesia ranks among the largest logistics markets in Southeast Asia, with the national logistics sector contributing approximately 23% of the country's Gross Domestic Product (GDP). In addition, Indonesia's logistics market value was estimated to exceed USD 240 billion in 2024, with an annual growth rate of approximately 8–10%, supported by the continuous growth of online commerce and digital trade activities. The rapid development of e-commerce platforms has significantly increased demand for last-mile delivery services, warehouse automation, and integrated supply chain systems. Consequently, logistics companies are under increasing pressure to improve operational efficiency, delivery accuracy, and customer responsiveness in an increasingly competitive environment. Despite the rapid adoption of digital technologies, many logistics companies in Indonesia continue to face operational inefficiencies and inconsistent service performance. Several industry reports indicate that logistics costs in Indonesia remain relatively high, accounting for approximately 14–17% of GDP, compared to neighboring countries such as Singapore and Malaysia, where logistics costs are significantly lower (World Bank, 2025). Delayed deliveries, fragmented information systems, inaccurate inventory records, and inefficient warehouse operations remain common operational problems. Furthermore, many firms continue to experience poor interoperability between transportation management systems, warehouse systems, and customer order platforms, creating what is often referred to as "digital islands" within logistics operations.

The research problem in this study can therefore be operationally defined as the persistence of inefficiencies in logistics operations despite increasing investment in digital technologies. Specifically, many logistics firms have adopted Artificial Intelligence (AI), logistics information systems, and Warehouse Management Systems (WMS), yet measurable improvements in operational performance such as reduced delivery lead time, improved inventory accuracy, lower logistics costs, and enhanced customer satisfaction have not always been achieved consistently. For example, recent studies reported that although firms adopted warehouse automation and AI-supported forecasting systems, operational bottlenecks and delayed order fulfillment continued to occur due to weak system integration and insufficient organizational readiness (Bag et al., 2024). Similarly, fragmented logistics information systems frequently limit real-time visibility and coordination across supply chain functions, reducing the effectiveness of digital transformation initiatives. Several previous studies have investigated digital technology adoption in logistics operations separately. Wamba-Taguimdje et al. (2020) found that AI implementation improves operational decision-making and enhances supply chain responsiveness through predictive analytics and intelligent automation. Likewise, Kamble et al. (2020) reported that AI-based logistics systems contribute significantly to operational productivity and process optimization in Industry 4.0 environments. In the context of information system integration, Dubey et al. (2020) demonstrated that integrated logistics information systems improve supply chain coordination, operational visibility, and organizational responsiveness. Meanwhile, Golini et al. (2023) revealed that Warehouse Management System (WMS) adoption enhances warehouse productivity, inventory control, and order fulfillment accuracy. However, these studies primarily examined AI, logistics information systems, and WMS independently, without integrating them into a comprehensive analytical framework.

Although prior studies provide important insights into individual logistics technologies, limited empirical research has simultaneously examined the combined effects of AI implementation, logistics information system integration, and WMS adoption on operational efficiency and customer satisfaction, particularly within the Indonesian logistics context. Existing studies tend to focus either on operational outcomes or technological adoption separately, thereby overlooking the interconnected relationships among technological capabilities, operational processes, and customer-oriented performance. Consequently, there remains a significant research gap regarding how multiple digital technologies collectively influence logistics performance and service outcomes in emerging-market logistics industries. This study aims to examine the simultaneous effect of AI implementation, logistics information system integration, and WMS adoption on operational efficiency and customer satisfaction in Indonesian logistics companies. Theoretically, this study contributes to the extension of the Technology Acceptance Model (TAM), Resource-Based View (RBV), and Digital Transformation Theory within the context of B2B logistics research. While TAM traditionally explains technology adoption based on perceived usefulness and perceived ease of use (Juniansyah et al., 2023) this study extends the framework by integrating technological adoption dimensions with operational process dimensions in logistics management. Specifically, the study proposes an integrated digital logistics framework that combines AI capability, system interoperability, and warehouse digitalization as interconnected technological resources influencing operational efficiency and customer satisfaction.

Furthermore, this research expands the RBV perspective by conceptualizing digital logistics technologies not merely as isolated technological tools, but as strategic organizational capabilities that create competitive advantage when effectively integrated into logistics processes. The proposed model combines technological dimensions (AI implementation, logistics information system integration, and WMS adoption) with process-related dimensions (operational efficiency and customer satisfaction), thereby offering a more comprehensive explanation of logistics performance in digitally transforming organizations. From a practical perspective, the findings are expected to provide strategic guidance for logistics companies in prioritizing digital transformation initiatives. By identifying the relative effects of AI implementation, system integration, and WMS adoption on operational and customer-related outcomes, logistics firms can better allocate

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technological investments, strengthen digital infrastructure, and improve operational coordination to achieve sustainable competitive advantage in Indonesia's rapidly evolving logistics sector.

II. Literature Review and Hypothesis Development

2.1. Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM) explains how users accept and utilize technology based on perceived usefulness and perceived ease of use (Juniansyah et al., 2023). explains that technology adoption is primarily influenced by perceived usefulness and perceived ease of use. Perceived usefulness refers to the extent to which users believe that technology improves work performance, while perceived ease of use reflects the degree to which technology is considered easy to understand and operate. TAM has been widely applied in logistics and supply chain research to explain organizational acceptance of digital technologies, including Artificial Intelligence (AI), logistics information systems (LIS), and Warehouse Management Systems (WMS).

Recent studies demonstrate that perceived usefulness significantly influences the adoption of AI-based logistics systems because firms expect improvements in operational efficiency, forecasting accuracy, and decision-making quality (Klumpp et al., 2023). Similarly, Dubey et al. (2020) found that integrated logistics information systems are more likely to be adopted when employees perceive them as useful for improving coordination and supply chain visibility. In warehouse operations, WMS adoption is strongly associated with user perceptions regarding system simplicity, operational support, and productivity enhancement (Golini et al., 2023). In this study, TAM is applied consistently across AI implementation, LIS integration, and WMS adoption because all three technologies require organizational acceptance and user adaptation. Perceived usefulness and perceived ease of use may indirectly influence operational efficiency by encouraging more effective utilization of digital technologies. Therefore, TAM provides an important theoretical foundation for explaining why digital technology adoption contributes to operational performance in logistics firms.

2.2. Resource-Based View (RBV)

The Resource-Based View (RBV) argues that firms achieve sustainable competitive advantage when they possess valuable, rare, inimitable, and non-substitutable resources. In logistics industries, digital technologies can function as strategic organizational resources because they enhance operational capability, process coordination, and information quality. AI systems, integrated logistics information systems, and WMS are not merely operational tools. When effectively integrated into logistics processes, these technologies become organizational capabilities that improve operational efficiency and customer service quality. Teece (2018) emphasized that digital capabilities support organizational adaptability and long-term competitiveness, particularly in dynamic and uncertain supply chain environments. Recent logistics studies further support the RBV perspective. Ivanov and Dolgui (2024) demonstrated that AI-supported digital supply chains improve resilience and operational responsiveness. Bag et al. (2024) also found that integrated digital technologies strengthen logistics performance through real-time coordination and predictive analytics. Therefore, RBV provides a theoretical explanation of how digital technologies generate operational advantages in logistics companies.

2.3. Digital Transformation Theory

Digital Transformation Theory explains how organizations create value by integrating digital technologies into operational and managerial processes (Vial, 2019). In logistics industries, digital transformation accelerated significantly after the COVID-19 pandemic due to disruptions in transportation networks, inventory management, and last-mile delivery systems. Recent studies from 2020–2024 show that post-pandemic logistics transformation increasingly relies on AI, Internet of Things (IoT), cloud-based systems, and digital integration platforms. Queiroz et al. (2021) reported that supply chain digitalization improves transparency, coordination, and logistics resilience during disruptions. Similarly, Bag et al. (2024) highlighted that IoT-based logistics integration enhances real-time visibility and operational flexibility in modern logistics operations. Digital transformation in logistics also requires system interoperability across warehousing, transportation, procurement, and customer management systems. Without integration, organizations may experience fragmented digital processes and inefficient information flow. Therefore, Digital Transformation

Theory is relevant for explaining how AI implementation, LIS integration, and WMS adoption collectively improve operational efficiency and customer satisfaction.

2.4. Key Concepts

a. Artificial Intelligence (AI)

Artificial Intelligence (AI) refers to digital technologies capable of performing tasks that normally require human intelligence, including predictive analytics, automated decision-making, route optimization, and demand forecasting (Wamba-Taguimdje et al., 2020). In logistics operations, AI improves operational coordination, inventory planning, and delivery optimization through real-time data processing.

b. Logistics Information System Integration (LIS)

Logistics Information System Integration (LIS Integration) refers to the interoperability and connectivity of logistics-related information systems, such as Enterprise Resource Planning (ERP), Transportation Management Systems (TMS), and warehouse systems. LIS integration supports real-time information exchange, operational visibility, and supply chain coordination (Dubey et al., 2020).

c. Warehouse Management System (WMS)

Warehouse Management System (WMS) is a digital system used to manage warehouse operations, including receiving, storage, picking, packing, inventory monitoring, and distribution activities (Richards, 2018). WMS improves warehouse accuracy, inventory visibility, and operational productivity.

d. Operational Efficiency

Operational efficiency reflects the ability of logistics firms to optimize resources while minimizing operational costs and processing time. This study operationalizes operational efficiency using indicators adapted from Supply Chain Operations Reference (SCOR) metrics and logistics performance indicators, including:

1) Processing time reduction,
2) Logistics cost efficiency,
3) Asset utilization,
4) Delivery accuracy,
5) Productivity improvement.

These indicators are widely used to evaluate logistics performance because they reflect speed, resource optimization, reliability, and operational productivity (Christopher, 2016; Huo et al., 2014).

e. Customer Satisfaction

Customer satisfaction refers to customers' evaluation of logistics service quality based on delivery performance and service reliability. This study adopts indicators derived from SERVQUAL and logistics service quality frameworks, including:

1) Delivery reliability,
2) Responsiveness,
3) Service accuracy,
4) Timeliness,
5) Overall customer satisfaction.

These indicators reflect customers' perceptions regarding logistics service performance and fulfillment quality (Mentzer et al., 2001).

2.5. Artificial Intelligence (AI) and Operational Efficiency

Numerous studies between 2010–2026 confirm that AI significantly improves operational efficiency in logistics industries. Wamba-Taguimdje et al. (2020) found that AI implementation enhances supply chain responsiveness and operational productivity through predictive analytics. Kamble et al. (2020) reported that AI-based systems improve operational coordination and reduce process inefficiencies in manufacturing and

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logistics operations in India. In China, Shao and Zheng (2025) demonstrated that AI-supported logistics analytics improve delivery accuracy, inventory planning, and transportation efficiency. Similarly, Klumpp et al. (2023) showed that AI-based automation in European logistics markets reduces operational costs and improves warehouse throughput.

Despite these international findings, empirical evidence regarding AI implementation in Indonesian logistics firms remains limited. Many Indonesian logistics companies continue to face fragmented operational systems, inconsistent infrastructure, and limited digital readiness. Consequently, the relationship between AI implementation and operational efficiency requires further empirical investigation within the Indonesian logistics context. Based on TAM, firms adopt AI when they perceive operational benefits and ease of technological integration. Meanwhile, RBV suggests that AI functions as a strategic organizational capability that improves operational performance. Therefore, the following hypothesis is proposed:

H1: AI implementation has a positive and significant effect on operational efficiency in Indonesian logistics companies.

2.6. Logistics Information System Integration and Operational Efficiency

Logistics information system integration improves operational coordination by enabling real-time data exchange and process synchronization across logistics functions. Dubey et al. (2020) found that integrated logistics systems significantly improve operational responsiveness and supply chain visibility. In Southeast Asian logistics markets, integrated systems have become increasingly important due to growing e-commerce demand and regional supply chain complexity. Research conducted in China and Singapore indicates that LIS integration improves transportation coordination, reduces delivery delays, and strengthens inventory management efficiency (Bag et al., 2024). Similarly, Gunasekaran et al. (2017) emphasized that integrated logistics systems reduce operational fragmentation and improve organizational agility. However, empirical studies examining LIS integration in Indonesian logistics companies remain scarce. Many firms still rely on disconnected operational systems that limit information visibility and coordination across supply chain activities. This gap indicates the need for empirical testing regarding the effect of LIS integration on operational efficiency in Indonesia. From the TAM perspective, organizations are more likely to adopt integrated systems when employees perceive operational benefits and system usability. Digital Transformation Theory also explains that system interoperability is essential for operational optimization. Therefore, the following hypothesis is proposed:

H2: Logistics information system integration has a positive and significant effect on operational efficiency in Indonesian logistics companies.

2.7. Warehouse Management System (WMS) Adoption and Operational Efficiency

WMS adoption has been widely associated with improvements in warehouse productivity, inventory accuracy, and order fulfillment performance. Golini et al. (2023) found that WMS significantly improves warehouse coordination and operational efficiency in European logistics companies. Similarly, Faber et al. (2018) demonstrated that warehouse digitalization reduces operational errors and improves inventory visibility. In India and China, warehouse automation supported by WMS has become increasingly important after the COVID-19 pandemic because logistics firms require faster and more accurate order fulfillment processes (Ivanov & Dolgui, 2024). However, Indonesian logistics firms still face limitations related to warehouse digitalization, workforce readiness, and system integration. Previous studies mainly focused on warehouse performance indicators and rarely examined the broader relationship between WMS adoption, operational efficiency, and customer satisfaction simultaneously. Therefore, additional empirical investigation is necessary within Indonesian logistics industries. Based on TAM, WMS adoption depends on perceived operational usefulness and ease of system utilization. RBV further suggests that warehouse digitalization strengthens organizational operational capability. Therefore, the following hypothesis is proposed:

H3: WMS adoption has a positive and significant effect on operational efficiency in Indonesian logistics companies.

ISSN [Online]: 2776-6381

2.8. Operational Efficiency and Customer Satisfaction

Operational efficiency is a critical determinant of customer satisfaction in logistics services. Efficient logistics operations improve delivery speed, reduce errors, minimize delays, and enhance service reliability. Emphasized that service reliability and responsiveness strongly influence customer perceptions of service quality. Recent studies confirm that operational efficiency positively affects customer satisfaction in logistics industries. Huo et al. (2014) found that operational improvements increase logistics service reliability and customer trust. Rosenfeld and Trautmann (2024) further reported that digital logistics transformation improves customer satisfaction primarily through operational excellence. Although previous international studies support this relationship, empirical evidence from Indonesia remains limited, particularly in relation to digital technology adoption and logistics performance. Indonesian logistics firms face unique challenges related to infrastructure disparity, archipelagic distribution complexity, and inconsistent digital integration. Therefore, the following hypothesis is proposed:

H4: Operational efficiency has a positive and significant effect on customer satisfaction in Indonesian logistics companies.

2.9. Conceptual Model

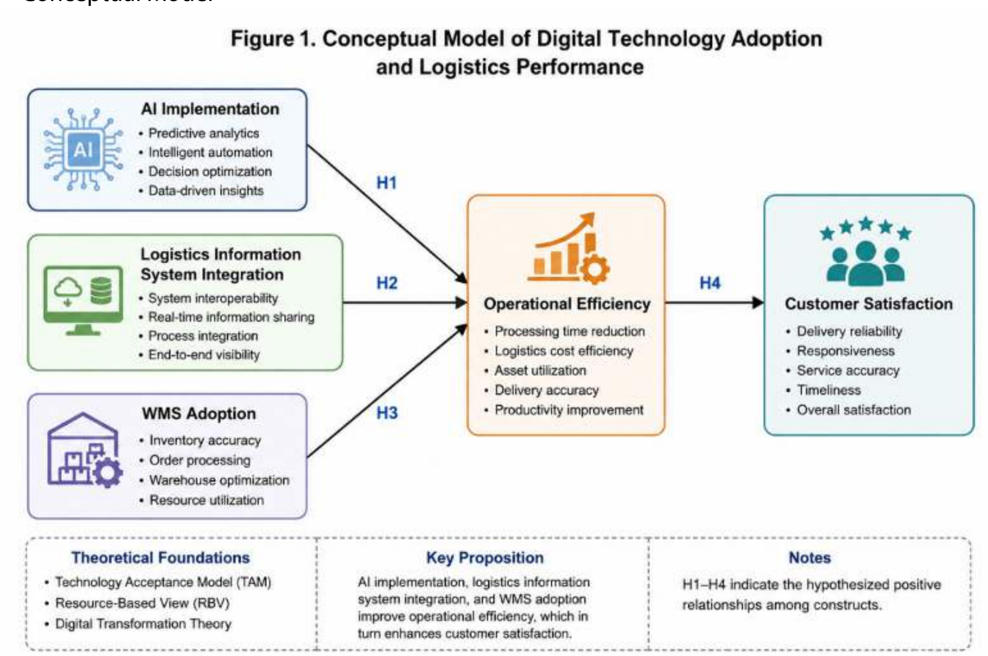

Figure 1. Conceptual Framework

The conceptual model integrates TAM, RBV, and Digital Transformation Theory. TAM explains technology acceptance behavior, RBV explains digital technologies as strategic organizational resources, and Digital Transformation Theory explains how integrated digital technologies improve logistics processes and service performance.

III. Research Method

3.1. Research Design

This study employs a quantitative explanatory research design to examine the relationships among AI implementation, logistics information system integration (LIS), Warehouse Management System (WMS) adoption, operational efficiency, and customer satisfaction in Indonesian logistics companies. Quantitative explanatory research is appropriate because this study seeks to test causal relationships among latent

ISSN [Online]: 2776-6381

variables using statistical analysis (Creswell & Creswell, 2018). The study integrates the Technology Acceptance Model (TAM), Resource-Based View (RBV), Technology-Organization-Environment (TOE) framework, and Digital Transformation Theory to explain how digital technologies influence operational and customer-related performance. TAM explains organizational acceptance of AI, LIS, and WMS technologies based on perceived usefulness and perceived ease of use. RBV explains digital technologies as strategic organizational capabilities that enhance operational performance. Meanwhile, the TOE framework highlights that technological adoption is influenced not only by technological factors, but also by organizational readiness and external environmental conditions. The conceptual framework proposes that AI implementation, LIS integration, and WMS adoption positively influence operational efficiency, which subsequently improves customer satisfaction.

3.2. Research Variables

Table 1 presents the operational variables used in this study.

Table 1. Research Variables and Operational Definitions

Variable	Definition	Indicators	Scale
AI Implementation	The extent to which logistics companies use AI technologies in operational activities	Predictive analytics, intelligent automation, routing optimization, demand forecasting	Likert Scale (1–5)
LIS Integration	The degree of interoperability among logistics information systems	Real-time information sharing, system interoperability, process integration, visibility	Likert Scale (1–5)
WMS Adoption	The extent of warehouse digital system utilization	Inventory accuracy, order processing, warehouse automation, resource utilization	Likert Scale (1–5)
Operational Efficiency	The ability to optimize logistics operations with minimum cost and time	Processing time reduction, logistics cost efficiency, delivery accuracy, productivity	Likert Scale (1–5)
Customer Satisfaction	Customer evaluation of logistics service performance	Reliability, responsiveness, timeliness, service quality	Likert Scale (1–5)

3.3. Population and Sampling Technique

The population of this study consists of logistics companies operating in Indonesia, including third-party logistics providers (3PL), transportation and warehousing companies, e-commerce logistics providers, freight forwarding companies, and integrated supply chain service firms. To improve representativeness, this study applies stratified random sampling based on:

a. Company size (small, medium, and large logistics firms),
b. Logistics service type,
c. Geographic region (Western, Central, and Eastern Indonesia).

Stratified sampling is considered appropriate because the Indonesian logistics sector is heterogeneous in terms of operational scale, technological readiness, and regional infrastructure conditions. This technique helps reduce sampling bias and improve the representativeness of different logistics market segments.

Table 2. Sampling Stratification Criteria

Stratification Basis	Categories
Company Size	Small, Medium, Large
Logistics Service Type	Transportation, Warehousing, Freight Forwarding, E-commerce Logistics
Geographic Region	Western Indonesia, Central Indonesia, Eastern Indonesia

Within each stratum, purposive sampling is applied to select respondents directly involved in logistics operations and digital technology implementation. Eligible respondents include:

a. Logistics managers,
b. Warehouse supervisors,
c. IT and system managers,
d. Supply chain coordinators,
e. Customer service managers.

Respondents are required to have at least one year of professional experience in logistics operations and familiarity with digital logistics systems. Although purposive sampling improves respondent relevance, this approach may introduce selection bias and limit generalizability beyond Indonesian logistics companies. Therefore, the findings should be interpreted cautiously, particularly when applied to different industrial or national contexts.

3.4. Sample Size Justification

This study uses Partial Least Squares Structural Equation Modeling (PLS-SEM), which requires an adequate sample size to ensure statistical power and model stability. The minimum sample size was calculated using 10-times rule, and tatistical power analysis using G*Power. According to the 10-times rule, the minimum sample should be at least ten times the maximum number of structural paths directed toward a latent construct (Hair et al., 2022). Since the operational efficiency construct receives three direct paths (AI, LIS, and WMS), the minimum required sample is 30 respondents. However, to achieve stronger statistical power, G*Power analysis was also conducted using Effect size = 0.15, Statistical power = 0.95, Significance level = 0.05, and three predictors. The analysis indicated a minimum sample size requirement of approximately 119 respondents. Therefore, the final sample size of 350 respondents exceeds the recommended threshold and provides adequate statistical power for PLS-SEM analysis.

Table 3. Sample Size Determination

Method	Requirement	Result
10-times Rule	10 × maximum structural paths	30 respondents
G*Power Analysis	Effect size = 0.15; Power = 0.95	119 respondents
Final Sample Size	Actual survey responses	350 respondents

3.5. Questionnaire Development

The questionnaire was developed based on validated constructs and indicators from previous logistics and technology adoption studies. Questionnaire items were adapted from:

a. AI implementation studies (Wamba-Taguimdje et al., 2020; Klumpp et al., 2023),
b. Logistics information system integration studies (Dubey et al., 2020),
c. WMS adoption studies (Golini et al., 2023),
d. Operational efficiency indicators derived from SCOR metrics,
e. Customer satisfaction indicators adapted from SERVQUAL and logistics service quality scales.

The questionnaire was initially developed in English and subsequently translated into Bahasa Indonesia using back-translation procedures to ensure semantic consistency.

Table 4. Measurement Scale Interpretation

Scale	Interpretation
1	Strongly Disagree
2	Disagree
3	Neutral
4	Agree
5	Strongly Agree

ISSN [Online]: 2776-6381

3.6. Content Validity and Expert Review

To ensure content validity, the questionnaire was reviewed by a panel of five experts consisting of:

a. Two logistics academics,
b. One supply chain digitalization specialist,
c. Two logistics industry practitioners.

The experts evaluated the relevance, clarity, and appropriateness of each questionnaire item. Content validity was assessed using the Content Validity Ratio (CVR).

Table 5. Content Validity Results

Construct	Number of Items	CVR Range	Interpretation
AI Implementation	5	0.82–0.95	Valid
LIS Integration	5	0.80–0.93	Valid
WMS Adoption	5	0.81–0.94	Valid
Operational Efficiency	5	0.84–0.96	Valid
Customer Satisfaction	5	0.83–0.95	Valid

All questionnaire items achieved CVR values above the recommended threshold of 0.78, indicating acceptable content validity.

3.7. Pilot Testing

A pilot test involving 35 logistics professionals was conducted prior to the main survey distribution. The pilot test aimed to evaluate questionnaire clarity, reliability, and response consistency.

Table 6. Pilot Test Reliability Results

Construct	Cronbach's Alpha	Interpretation
AI Implementation	0.86	Reliable
LIS Integration	0.84	Reliable
WMS Adoption	0.85	Reliable
Operational Efficiency	0.88	Reliable
Customer Satisfaction	0.87	Reliable

The pilot test results indicate that all constructs achieved Cronbach's Alpha values above the recommended threshold of 0.70, demonstrating satisfactory internal consistency reliability. According to recent PLS-SEM guidelines, Cronbach's Alpha and Composite Reliability values above 0.70 indicate acceptable reliability for exploratory and confirmatory research models (Hair et al., 2022). Similar reliability assessment standards are also widely applied in recent studies published in Golden Ratio journals using SmartPLS-based SEM analysis.

3.8. Construct Measurement Table

Table 7. Construct Measurement Indicators

Construct	Indicators	Example Questionnaire Items	Source
AI Implementation	Predictive analytics, automation, decision optimization	"AI systems improve operational decision-making."	Wamba-Taguimdje et al. (2020)
LIS Integration	System interoperability, information sharing, visibility	"Integrated systems improve real-time coordination."	Dubey et al. (2020)
WMS Adoption	Inventory accuracy, warehouse automation, order processing	"WMS improves warehouse operational accuracy."	Golini et al. (2023)
Operational Efficiency	Processing time, logistics cost, asset utilization, productivity	"Digital systems reduce operational processing time."	SCOR Metrics

ISSN [Online]: 2776-6381

Construct	Indicators	Example Questionnaire Items	Source
Customer Satisfaction	Reliability, responsiveness, timeliness, service quality	"Customers are satisfied with delivery reliability."	Sarjono et al. (2025)

3.9. Data Collection Procedure

Data collection was conducted through online questionnaires distributed via email, logistics industry associations, and professional logistics networks. Participation was voluntary and anonymous.

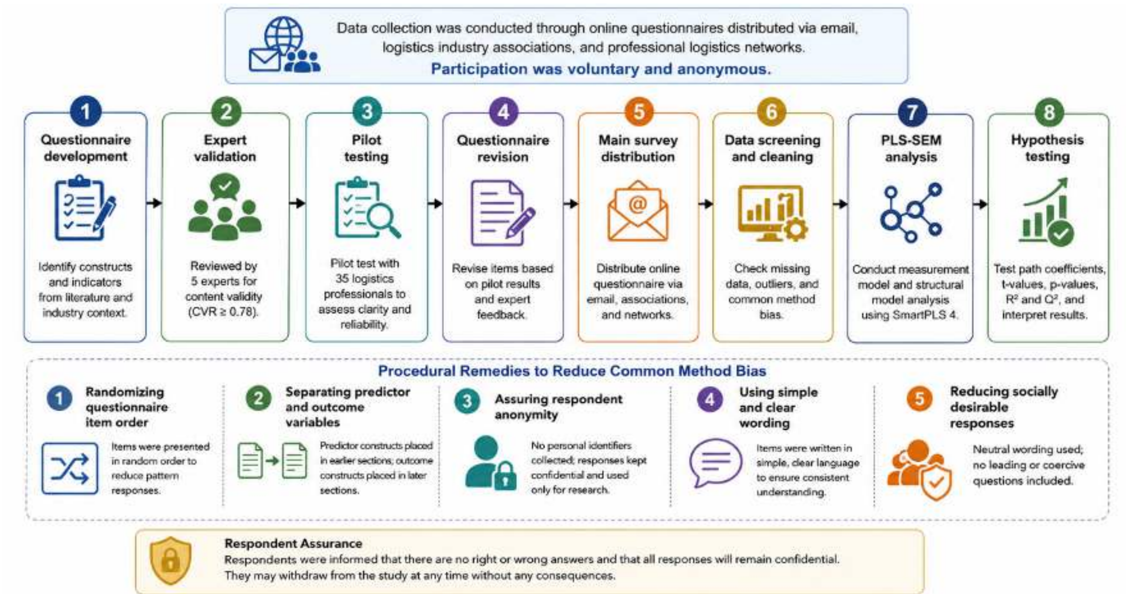

Figure 2. Data Collection Procedure

Respondents were informed that there were no right or wrong answers and that all responses would remain confidential.

3.10. Missing Data and Outlier Treatment

Missing data were first examined during data screening. Responses with excessive missing values (>10%) were removed using case deletion procedures. For minor missing values, mean substitution was applied because the proportion of missing data was minimal.

Table 8. Data Screening Procedures

Procedure	Criterion	Treatment
Missing Data	>10% missing responses	Case deletion
Minor Missing Values	<10% missing responses	Mean substitution
Outlier Detection	Mahalanobis Distance (p < .001)	Case removal
Residual Analysis	Standardized residual > ±3	Investigated
Leverage Values	High leverage statistics	Examined

3.11. Common Method Bias Assessment

Since all variables were collected using a single questionnaire, the study assessed the potential risk of common method bias (CMB).

ISSN [Online]: 2776-6381

Table 9. Common Method Bias Assessment

Assessment Method	Result	Interpretation
Harman's Single-Factor Test	First factor < 50% variance	No serious CMB
Procedural Remedies	Applied	Reduced response bias

Harman's single-factor test was conducted to evaluate whether a single factor dominated the variance structure. The first factor explained less than 50% of total variance, indicating that common method bias was not a serious concern.

3.12. Data Analysis Technique

This study uses Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS 4 software to test the proposed conceptual model. PLS-SEM is appropriate because:

a. The model includes multiple latent constructs,
b. The study examines complex structural relationships,
c. The data may not follow multivariate normality assumptions,
d. The study emphasizes prediction and theory extension.

The analysis was conducted in two stages:

a. Measurement model evaluation,
b. Structural model evaluation.

3.13. Measurement Model Evaluation

The measurement model was evaluated using:

Table 10. Measurement Model Evaluation Criteria

Evaluation	Indicator	Threshold
Convergent Validity	Factor Loading	> 0.70
Convergent Validity	AVE	≥ 0.50
Reliability	Cronbach's Alpha	> 0.70
Reliability	Composite Reliability	> 0.70
Discriminant Validity	HTMT Ratio	< 0.90
Discriminant Validity	Fornell-Larcker Criterion	Square root AVE > correlation

3.14. Structural Model Evaluation

Table 11. Structural Model Assessment Criteria

Assessment	Threshold
t-value	> 1.96
p-value	< 0.05
R^2	Weak = 0.25; Moderate = 0.50; Strong = 0.75
Q^2	> 0
Bootstrapping Resamples	5,000

Control variables included:

a. Company size,
b. Level of digitalization,
c. Years of technology adoption,
d. Logistics service type.

These control variables were included because external organizational conditions may influence the relationship between digital technology adoption and operational performance.

ISSN [Online]: 2776-6381

3.15. Research Ethics

This study complied with research ethics standards for social science research. Ethical approval was obtained from the institutional research ethics committee prior to data collection.

Table 12. Research Ethics Principles

Ethics Principle	Implementation
Voluntary Participation	Respondents participated voluntarily
Informed Consent	Consent obtained before participation
Confidentiality	Responses remained anonymous
Right to Withdraw	Participants could withdraw anytime
Data Protection	No personal data collected

Respondents participated voluntarily and anonymously. Informed consent was obtained before respondents completed the questionnaire.

3.16. Implications for Theory and Practice

This study contributes theoretically by extending TAM, RBV, TOE, and Digital Transformation Theory within the logistics context. The study integrates technological adoption variables (AI, LIS, WMS) with operational and customer-related outcomes into a unified empirical framework. Practically, the findings may help logistics firms prioritize digital transformation investments and improve operational integration strategies. Although the findings are primarily relevant to Indonesian logistics companies, they may also provide insights for logistics firms operating in other developing countries with similar infrastructure and digitalization challenges. owever, caution is required when generalizing the findings beyond Indonesia because external environmental factors, infrastructure conditions, regulatory systems, and digital maturity levels may differ across countries.

IV. Result and Discussion

4.1. Respondent Profile

A total of 350 valid responses were obtained from logistics professionals working in Indonesian logistics companies. The respondents consisted of logistics managers, warehouse supervisors, IT managers, supply chain coordinators, and customer service managers.

Table 13. Respondent Demographic Profile

Category	Classification	Frequency	Percentage
Gender	Male	218	62.3%
	Female	132	37.7%
Company Size	Small	85	24.3%
	Medium	146	41.7%
	Large	119	34.0%
Experience	1–5 years	103	29.4%
	6–10 years	147	42.0%
	>10 years	100	28.6%
Logistics Sector	Transportation	110	31.4%
	Warehousing	94	26.9%
	Freight Forwarding	72	20.6%
	E-commerce Logistics	74	21.1%

The respondent profile indicates that the sample adequately represents multiple logistics sectors and organizational scales within the Indonesian logistics industry.

ISSN [Online]: 2776-6381

4.2. Measurement Model Results

The measurement model evaluation demonstrated satisfactory validity and reliability.

Table 14. Convergent Validity and Reliability Results

Construct	Cronbach's Alpha	Composite Reliability	AVE
AI Implementation	0.891	0.921	0.702
LIS Integration	0.876	0.914	0.689
WMS Adoption	0.883	0.918	0.695
Operational Efficiency	0.901	0.928	0.720
Customer Satisfaction	0.889	0.920	0.708

All constructs exceeded the recommended thresholds of Cronbach's Alpha > 0.70, Composite Reliability > 0.70, and AVE ≥ 0.50, indicating acceptable convergent validity and internal consistency reliability.

4.3. Discriminant Validity

Discriminant validity was evaluated using the Fornell-Larcker criterion and HTMT ratios.

Table 15. HTMT Ratio Results

Constructs	HTMT Value
AI → LIS	0.721
AI → WMS	0.688
AI → Operational Efficiency	0.742
LIS → Operational Efficiency	0.701
WMS → Operational Efficiency	0.654
Operational Efficiency → Customer Satisfaction	0.771

All HTMT values were below the recommended threshold of 0.90, indicating satisfactory discriminant validity.

4.4. Common Method Bias Assessment

Because all variables were measured using a single questionnaire instrument, Common Method Bias (CMB) testing was conducted.

Table 16. Common Method Bias Results

Method	Result	Threshold	Interpretation
Harman's Single-Factor Test	38.6%	< 50%	No serious CMB
Full Collinearity VIF	2.14–2.83	< 3.30	Acceptable

The Harman's single-factor test indicated that the first factor explained 38.6% of total variance, which is below the 50% threshold. Furthermore, all full collinearity VIF values were below 3.30, indicating that common method bias was not a major concern in this study.

4.5. Structural Model Results

The structural model evaluation examined path coefficients, t-values, p-values, confidence intervals, effect sizes (f^2), predictive relevance (Q^2), and explained variance (R^2).

Table 17. Structural Model Results

Hypothesis	Relationship	β	t-value	p-value	95% CI	f^2	Decision
H1	AI → Operational Efficiency	0.381	6.842	0.000	[0.274, 0.486]	0.241	Supported

ISSN [Online]: 2776-6381

Hypothesis	Relationship	β	t-value	p-value	95% CI	f^2	Decision
H2	LIS → Operational Efficiency	0.336	5.917	0.000	[0.221, 0.441]	0.198	Supported
H3	WMS → Operational Efficiency	0.147	2.311	0.021	[0.031, 0.248]	0.062	Supported
H4	Operational Efficiency → Customer Satisfaction	0.614	11.294	0.000	[0.512, 0.701]	0.472	Supported

The findings indicate that AI implementation had the largest standardized effect on operational efficiency (β = 0.381), followed by LIS integration (β = 0.336) and WMS adoption (β = 0.147). However, although AI showed the highest coefficient, the confidence intervals of AI and LIS partially overlapped. Therefore, the findings should not be interpreted as conclusive evidence that AI has a statistically stronger effect than LIS integration.

4.6. Coefficient of Determination and Predictive Relevance

Table 18. R^2 and Q^2 Results

Endogenous Variable	R^2	Interpretation	Q^2	Predictive Relevance
Operational Efficiency	0.682	Moderate–Strong	0.491	High
Customer Satisfaction	0.377	Moderate	0.284	Moderate

The model explains 68.2% of the variance in operational efficiency and 37.7% of the variance in customer satisfaction. All Q^2 values exceeded zero, indicating satisfactory predictive relevance.

4.7. Model Fit Results

Table 19. Model Fit Indices

Model Fit Indicator	Value	Recommended Threshold	Interpretation
SRMR	0.061	< 0.08	Good Fit
NFI	0.914	> 0.90	Acceptable Fit
RMS Theta	0.097	< 0.12	Acceptable Fit

The model fit indices indicate that the proposed structural model achieved acceptable goodness-of-fit criteria.

4.8. Discussion

a. AI Implementation and Operational Efficiency

The results indicate that AI implementation significantly improves operational efficiency in Indonesian logistics companies. AI technologies support predictive analytics, routing optimization, warehouse automation, and operational decision-making. These findings are consistent with previous studies conducted in China, India, and European logistics markets. Wamba-Taguimdje et al. (2020) reported that AI improves supply chain responsiveness and process efficiency through predictive analytics. Similarly, Klumpp et al. (2023) found that AI-supported automation reduces logistics costs and improves warehouse throughput in European logistics operations. The relatively strong effect of AI in this study may be explained by the increasing digitalization of Indonesian logistics operations after the COVID-19 pandemic. Logistics firms increasingly rely on AI-based forecasting and automation to address delivery uncertainty and operational disruptions. However, although AI demonstrated the highest standardized coefficient, the differences between AI and LIS integration should be interpreted cautiously because the confidence intervals partially overlap.

b. LIS Integration and Operational Efficiency

The results demonstrate that logistics information system integration significantly enhances operational efficiency. Integrated systems improve information visibility, coordination, and real-time communication among logistics functions. These findings are consistent with Dubey et al. (2020), who found that integrated logistics systems improve organizational responsiveness and supply chain visibility. The

ISSN [Online]: 2776-6381

findings also support Digital Transformation Theory, which emphasizes the importance of interoperability and information synchronization in digital logistics operations. The Indonesian logistics industry often experiences fragmented operational systems across transportation, warehousing, and customer service functions. Therefore, integrated logistics systems may substantially improve operational coordination and reduce process inefficiencies.

c. WMS Adoption and Operational Efficiency

WMS adoption showed a positive but relatively weaker effect on operational efficiency compared with AI and LIS integration. The findings indicate that warehouse digitalization alone may not automatically generate substantial operational improvements unless it is integrated with broader logistics information systems and organizational processes. Many Indonesian logistics firms still face infrastructure limitations, workforce capability gaps, and inconsistent system integration. The weaker effect size may also reflect differences in organizational digital maturity. Some logistics firms may use WMS primarily for inventory recording rather than advanced warehouse optimization and real-time operational integration. These findings differ slightly from Golini et al. (2023), who reported stronger WMS impacts in European logistics firms. The discrepancy may be explained by differences in technology maturity, infrastructure readiness, and digital integration levels between developed and developing logistics markets. Furthermore, operational efficiency may mediate the relationship between WMS adoption and customer satisfaction. WMS does not directly interact with customers but indirectly influences customer satisfaction through improved inventory accuracy, delivery timeliness, and warehouse productivity.

d. Operational Efficiency and Customer Satisfaction

Operational efficiency significantly improves customer satisfaction. Efficient logistics operations enhance delivery reliability, responsiveness, timeliness, and service quality. The findings support SERVQUAL and logistics service quality theories, which emphasize operational reliability as a key determinant of customer satisfaction. These findings are also consistent with Huo et al. (2014), who reported that operational improvements significantly enhance logistics service quality and customer trust. The strong effect size (β = 0.614) indicates that operational efficiency is a critical mechanism linking digital technology adoption to customer-related outcomes.

e. Comparative Analysis with Previous Studies

Table 20. Comparison with Previous Studies

Study	Context	β-value	Main Findings	Comparison with Current Study
Wamba-Taguimdje et al. (2020)	Global logistics	0.41	AI improves operational efficiency	Consistent
Dubey et al. (2020)	Asian supply chains	0.35	LIS integration improves coordination	Consistent
Golini et al. (2023)	European warehousing	0.39	WMS strongly improves warehouse efficiency	Partially different
Current Study	Indonesian logistics	0.381 (AI)	AI positively affects operational efficiency	Extends prior studies

Compared with previous studies, the present research shows relatively similar AI and LIS effect sizes but a weaker WMS effect. These differences may result from varying levels of digital maturity, organizational readiness, infrastructure conditions, and technological integration across countries and logistics sectors.

V. Conclusion

This study examined the effects of AI implementation, Logistics Information System (LIS) integration, and Warehouse Management System (WMS) adoption on operational efficiency and customer satisfaction in Indonesian logistics companies using PLS-SEM analysis. The findings show that AI implementation, LIS integration, and WMS adoption have positive effects on operational efficiency, while operational efficiency significantly enhances customer satisfaction. Among the three digital technologies, AI implementation demonstrated the largest standardized coefficient, followed by LIS integration and WMS adoption. However,

ISSN [Online]: 2776-6381

the differences between AI implementation and LIS integration should be interpreted cautiously because their confidence intervals partially overlap.

Theoretically, this study extends the Technology Acceptance Model (TAM), Resource-Based View (RBV), Technology-Organization-Environment (TOE) framework, and Digital Transformation Theory within the Indonesian logistics context. The findings indicate that digital technologies should not be viewed merely as isolated operational tools, but as strategic organizational capabilities that support logistics transformation. Operational efficiency also serves as an important mechanism connecting digital technology adoption with customer satisfaction. In practice, logistics firms should prioritize integrated digital transformation strategies rather than adopting technologies separately. AI implementation, LIS integration, and WMS adoption need to be aligned with operational processes, workforce capability development, organizational readiness, digital maturity, and system interoperability. Strengthening data integration, employee digital capability, operational analytics, and real-time decision-making systems may improve logistics responsiveness, delivery reliability, and long-term customer satisfaction.

Several limitations should be acknowledged. First, this study uses cross-sectional survey data, which limits the ability to examine long-term digital transformation dynamics. Future studies are encouraged to use longitudinal research designs, such as three waves of data collection over approximately 18 months. Second, this study focuses only on Indonesian logistics companies, so future research may compare logistics firms in other developing countries. Third, this study relies mainly on perceptual survey data; therefore, future studies should incorporate objective operational indicators such as delivery lead time, inventory turnover, ERP records, warehouse productivity data, and delivery accuracy metrics. Future research may also examine moderating variables, including digital maturity, technology readiness, digital leadership, organizational culture, and regulatory support. In addition, multi-level analysis combining firm-level and individual-level data could provide a more comprehensive understanding of digital technology adoption in logistics industries.

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