OPTIMIZING INVENTORY MANAGEMENT THROUGH DIGITAL TRANSFORMATION INTEGRATION IN THE INDONESIAN AIRCRAFT MRO INDUSTRY

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Abstract. *This study originates from the issue of substantial financial losses experienced by a Maintenance, Repair, and Overhaul (MRO) company in Indonesia in 2024 due to delays in the arrival of spare parts. These delays subsequently affected the timeliness of Return to Service (RTS) for aircraft undergoing C-Check maintenance, resulting in a high number of Aircraft on Ground (AOG) cases. This research aims to analyze the effect of digital transformation integration, represented by three main variables: Artificial Intelligence (AI)-based forecasting, Enterprise Resource Planning (ERP) flexibility, and Big Data, on inventory management optimization in the Indonesian aircraft MRO industry. A quantitative method was employed, with the analysis conducted using SmartPLS software. The study involved 120 respondents from the management level of aircraft MRO companies in Indonesia. The findings reveal that among the three digital transformation variables tested, only ERP flexibility has a significant impact on inventory management optimization. Specifically, the ERP feature that allows for user customization—which emerged as the strongest indicator within the ERP flexibility variable—has a substantial influence on inventory management optimization. Meanwhile, AI-based forecasting and Big Data did not demonstrate significant effects. These findings indicate that implementing digital transformation through ERP flexibility can enhance inventory management optimization, thereby enabling aircraft to return to service on time due to the availability of spare parts. This research is expected to serve as a practical reference for managers in the MRO industry in designing digital transformation strategies to achieve more effective inventory management.*

Keywords: *Artificial Intelligence, ERP Flexibility, Big Data, Inventory Management, Aircraft MRO Industry*

1. INTRODUCTION

Inventory management plays a crucial role in modern business operations, as it can make a significant contribution to profitability or conversely become a major obstacle to operational activities. Effective inventory management serves as the foundation for business sustainability, particularly in the context of perishable goods and the dynamics of multi-channel supply chains (Cao, 2023). Inaccurate inventory levels can have serious operational impacts, including production disruptions and financial losses (Hossain et al., 2023). This issue is further compounded by demand fluctuations and supply chain complexity, which increase the risks of both stockouts and excess inventory, as described in various studies on inventory routing problems and demand variability (Song et al., 2023; Ajibade et al., 2022). Addressing inventory management challenges is therefore critical, as failure to do so may significantly impact a company's financial sustainability, necessitating the implementation of advanced strategies such as reinforcement learning to optimize inventory control practices (Piao et al., 2023). Accordingly, effective inventory control remains a primary focus for organizations seeking to enhance operational efficiency and maintain competitiveness in the market.

Digital transformation fundamentally refers to the utilization of advanced technologies to comprehensively transform business processes, making them more adaptive, integrated, and data-driven (Vial, 2022). Within the context of supply chain and inventory management, digital transformation theory emphasizes the importance of implementing artificial intelligence (AI) to support precise demand forecasting, which can minimize supply uncertainty (Fekih & Boubaker, 2023). Meanwhile, ERP flexibility is regarded as a key element that enables organizations to adjust modules, workflows, and cross-departmental data integration in response to evolving operational needs (Harbi & El Amrani, 2023). In addition, Big Data serves as a foundational pillar within digital transformation theory by providing a basis for real-time, data-driven decision-making through the processing of large, diverse, and high-velocity data volumes (Ali et al., 2022). The synergy of these three variables reinforces the theory that digital transformation extends beyond mere technology adoption to include the integration of AI, ERP flexibility, and Big Data in supporting process innovation, enhancing responsiveness, and creating sustainable added value.

The utilization of AI-based demand forecasting, ERP flexibility, and Big Data has significantly transformed inventory management by addressing various challenges associated with controlling inventory levels, which previously relied on manual processes prone to inefficiency and errors. Through Big Data analytics, companies can analyze large-scale data to gain real-time insights into inventory levels and demand forecasts (Zou et al., 2024; Tang, 2024). The implementation of AI and machine learning algorithms further enhances predictive capabilities, enabling proactive inventory management to mitigate the risks of overstocking or stockouts (Albqowr et al., 2022). Furthermore, ERP systems enriched with AI strengthen supply chain integration, ensuring that inventory decisions are well-coordinated with overall business operations (Adeyeye & Akanbi, 2024). This technological combination not only streamlines inventory control but also improves financial outcomes through cost efficiencies and enhanced service levels (Li & Venkatachalam, 2022). Consequently, the effective application of AI, ERP, and Big Data represents a strategic transformation in inventory management that enables businesses to swiftly adapt to market dynamics and consumer demand.

In 2024, an Indonesia-based aircraft Maintenance, Repair, and Overhaul (MRO) company faced significant financial losses amounting to millions of US dollars due to delays in aircraft maintenance completion, which were caused by uncertainty and unavailability of spare parts for C-Check maintenance. C-Check is a comprehensive inspection covering an aircraft's structure, systems, and interior, conducted every 18–24 months or every 4,000–6,000 flight hours, with a typical duration of one to two weeks (7–14 days) (Kinnison & Siddiqui, 2021; Boeing MRO Facts). This issue not only disrupted maintenance operations but also undermined customer trust due to interrupted flight schedules reliant on fleet readiness. Boeing Commercial Airplanes (2022), through internal white papers and industry reports frequently cited in MRO literature, estimates that losses from Aircraft On Ground (AOG) for narrow-body aircraft such as the Boeing 737 can exceed USD 25,000 per day, including lost passenger revenue, passenger accommodation costs, crew rescheduling, and compensation.

Table 1. Maintenance Status of Aircraft with Long AOG Status

No	AC-Reg	Maintenance Type	Remaining Days	Estimated Loss ($)
1	PK-*GR	C-Check	> 1 year	$ 8.775.000,00
2	PK-*GM	C-Check	> 6 months	$ 4.200.000,00
3	PK-*JI	C-Check	> 6 months	$ 4.200.000,00
4	PK-*HT	C-Check	> 6 months	$ 4.200.000,00
5	PK-*FR	C-Check	> 6 months	$ 4.200.000,00
6	PK-*FQ	C-Check	> 6 months	$ 4.200.000,00
7	PK-*FF	C-Check	> 6 months	$ 4.200.000,00
				$33.975.000,00

(Source: Indonesia-Based MRO Company Data (2024)

As shown in Table 1, seven aircraft have not yet returned to service (RTS) due to spare parts arrival uncertainty, with one aircraft grounded for over a year, incurring a loss of USD 8.775 million, and six others grounded for more than six months. The total loss for these seven aircraft exceeds USD 33.975 million, equivalent to approximately IDR 543 billion (exchange rate: IDR 16,000/USD), and will continue to grow if the aircraft remain grounded. One indication of spare part arrival uncertainty is linked to vendor performance for Rotable/Repairable (RO) parts. An analysis of spare part shipments from various vendors for Rotable parts is presented below:

Table 2. Average TAT Status of RO Vendors

No	Vendor Area	Qty	Avg TAT RO	KPI	Gap
1	Vendor International	12872	117	95	22
2	Vendor Domestik	2245	34	95	-63
3	Shop Internal	30367	26	65	-48

(Source: Indonesia-Based MRO Company Data (2024)

Table 2 shows that average spare part deliveries from vendors exceeded KPI targets. The delivery gap for international vendors surpassed the KPI by 22 days. A more detailed breakdown reveals that 69 RO items from international vendors had TATs exceeding 300 days, while 7,328 items had TATs ranging from 96 to 299 days which can be seen in table 3 below:

Table 3. RO Vendor TAT Status by Day Category

No	Vendor Area	< 65 Days	66 sd 95 Days	96 sd 299 Days	>300 Days
1	Vendor International	2184	3291	7328	69
2	Vendor Domestik	1962	185	98	-
3	Shop Internal	25927	2014	2412	14

(Source: Indonesia-Based MRO Company Data (2024)

Interestingly, spare part inventory status recorded in the company's eMRO system (SAP used by the MRO company) is presented below:

Table 4. Inventory Status

No	Spare Parts Inventory	Items	%
1	0-90 Days	14684	24,33%
2	91-1 Year	13896	23,03%
3	1-3 Years	13432	22,26%
4	>3 Years	18332	30,38%
		60344	**100%**

(Source: Indonesia-Based MRO Company Data (2024)

As shown in Table 4, a significant number of spare parts are stored in the warehouse, with 18,332 items (30.38%) having been stagnant for over three years. A stock opname revealed that many spare parts were mismatched between the system inventory and the physical stock, including obsolete spare parts incompatible with current aircraft, parts missing documentation and thus unreleasable by Quality Control, expired or unserviceable parts, and modified parts still registered in the system. An internal investigation found that the company's method of consolidating data across relevant units for controlling aircraft maintenance spare part arrivals remains conventional, relying on Microsoft Excel without the support of digital transformation for data consolidation.

2. LITERATURE REVIEW

Previous research on the impact of digital transformation through Artificial Intelligence (AI) on inventory management has been conducted by Choudhuri (2022), who emphasized the transformative potential of AI in optimizing inventory management and highlighted the importance for companies to adopt this technology to maintain competitiveness in the rapidly evolving global market. Furthermore, the study by Badhan et al. (2024) demonstrated that AI-based inventory management systems hold significant potential for improving healthcare services in the United States and supporting the development of successful logistics operations. Adetula and Akanbi (2023) confirmed that the implementation of AI-based predictive analytics can significantly enhance demand forecasting accuracy and inventory management optimization, particularly within SME supply chains, by leveraging real-time data integration, machine learning algorithms, and adaptive predictive approaches. Another study by Kamble and Tewari (2022) also highlighted the impact of Big Data on inventory optimization but emphasized the need for categorization, contextual classification, data cleansing, and quality audits before predictive analysis can be effectively performed. In addition, the research by Pradata and Ernawati (2024) concluded that the implementation of Enterprise Resource Planning (ERP) systems has a positive effect on improving inventory management performance.

Several other studies have underscored the challenges in implementing AI-based forecasting, ERP flexibility, and Big Data in inventory management, particularly regarding integration complexity, resource constraints, and the persistence of traditional practices. Zhu and Liu (2024) found that efforts to increase inventory flexibility through AI may potentially lead to system irregularities, thus failing to achieve the desired efficiency. Zhao et al. (2023) revealed that dependence on deterministic algorithms within ERP systems can render inventory planning less adaptive to demand fluctuations. Meanwhile, Wahedi et al. (2023) asserted that SMEs in the MRO sector often face financial and infrastructural limitations, resulting in AI adoption that is frequently partial and still reliant on conventional decision-making. Memon et al. (2022) also observed that traditional ERP approaches continue to be maintained because they are considered more reliable and cost-effective, albeit less innovative compared to AI-based solutions. Although Big Data holds considerable potential for inventory optimization, its implementation requires organizational readiness and thorough evaluation to ensure effective and sustainable operations (Putra & Arifin, 2021).

This study aims to analyze the integration of three digital transformation variables; Artificial Intelligence (AI)-based forecasting, Enterprise Resource Planning (ERP) flexibility, and Big Data—in the aircraft MRO (Maintenance, Repair, and Overhaul) industry, particularly in Indonesia, so that aircraft maintenance processes can achieve Return To Service (RTS) in accordance with the established schedule due to well-managed and optimized inventory management that ensures timely availability of spare parts. Previous studies have typically examined and analyzed the AI, ERP flexibility, and Big Data variables only partially in relation to inventory management optimization. In this study, in addition to the different research context—focusing on the aircraft MRO industry rather than the more commonly studied manufacturing sector—the variables are tested both partially and simultaneously. Thus, the novelty of this research lies in its focus on the simultaneous integration of these three technological elements, specifically applied to the context of optimizing spare parts inventory management within Indonesia's aircraft MRO industry, an area that has received limited attention in prior studies. Therefore, this research is expected to contribute to the enrichment of the literature on digital technology-based inventory management in the aircraft MRO sector, which remains relatively underexplored compared to the manufacturing or general logistics sectors.

3. RESEARCH METHODS

The research methodology constitutes a scientific approach for data collection with specific purposes and significance. This scientific approach encompasses four key elements: scientific techniques, data, objectives, and specific benefits. In this study, a quantitative research method is applied. According to Sugiyono, 2021, quantitative research is a scientific research method that involves phenomena that can be measured, objective, rational, and systematic. This method is employed to investigate a specific population or sample, collect data using research instruments, and subsequently test hypotheses through quantitative or statistical data analysis.

A total of 38 questions were formulated based on all indicators included in the questionnaire. The questionnaire was developed using a five-point Likert scale and designed around four variables elaborated through the indicators within the conceptual research model. The questionnaire was translated into Indonesian to ensure that respondents clearly understood the questions presented. The sample size for the questionnaire was determined by multiplying the largest number of indicators by ten, as recommended by Hair et al. (2019). The largest number of indicators in this study is twelve, resulting in a sample size of 120 respondents. The questionnaire was distributed online to professionals working in MRO companies located in the Riau Islands Province, Banten Province, and Jakarta Province, who has a position at management level. The respondents consisted of logistics managers, assistant managers, or supervisors; warehouse managers, assistant managers, or supervisors; procurement managers, assistant managers, or supervisors; and distribution managers, assistant managers, or supervisors in the MRO industry, as they possess sufficient knowledge of the variables under study. Approximately two weeks after the questionnaire was distributed, 120 completed responses were collected and deemed valid for further analysis.

The data analysis in this study was conducted using Variance-based Partial Least Squares Structural Equation Modeling (PLS-SEM). The PLS-SEM model investigates the relationships among variables. The measurement model was evaluated using SmartPLS 3.0 to ensure the validity and reliability of the construct variables, as proposed by Sarstedt et al. (2016). Despite the non-normal distribution of the data, this study validated the conceptual model through the implementation of PLS-SEM (Hair et al., 2022; Ringle et al., 2022).

The figure below presents the conceptual research model, which is based on a comprehensive literature review and rigorous hypothesis testing from various previous studies.

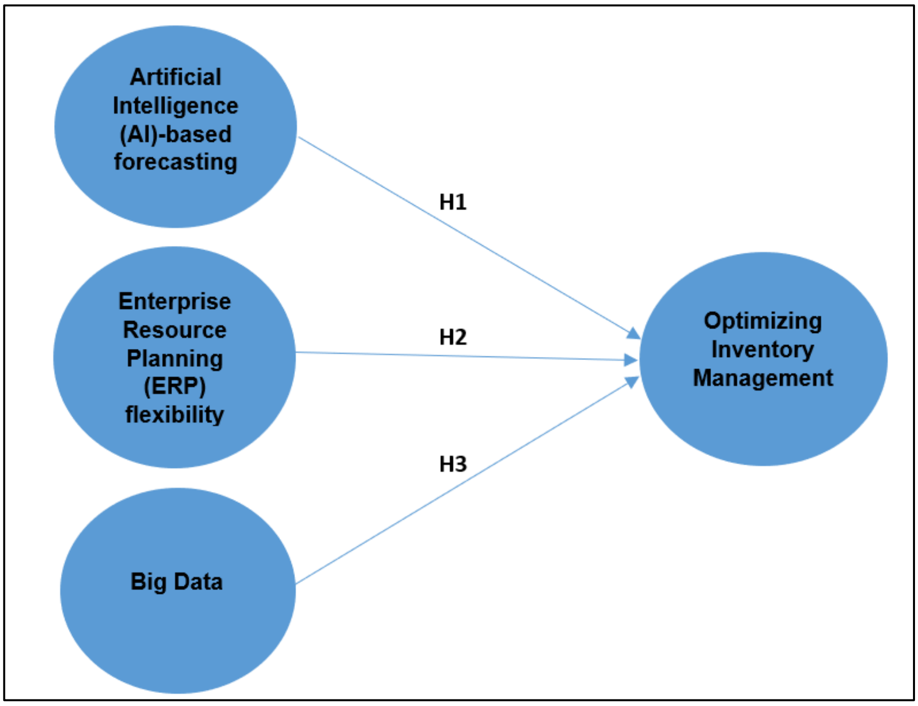

Figure 1. Theoretical Framework

4. RESULTS AND DISCUSSION

SmartPLS was employed to evaluate the research model through two main stages, namely the measurement model (outer model) and the structural model (inner model). In the measurement model, convergent validity is ensured when factor loadings are ≥ 0.70 and the Average Variance Extracted (AVE) is ≥ 0.50, while discriminant validity is tested by verifying that the correlations between latent constructs are lower than the square root of the AVE in accordance with the Fornell–Larcker criterion. Reliability is further confirmed through Composite Reliability and Cronbach's Alpha, both of which should be ≥ 0.70. Subsequently, the structural model aims to examine the relationships between latent variables using t-statistic values, p-values, and the R-squared (R^2) coefficient—where an $R^2 \geq 0.75$ indicates strong explanatory power, approximately 0.50 indicates moderate, and around 0.25 is considered weak. Hair et al. (2022) recommend a significance threshold of $t > 1.65$ and $p < 0.05$ to test the relationships between constructs at the 5% significance level.

4.1 Results of the Outer Measurement Model

Based on the findings presented in Table 5, among a total of 38 indicators, several indicators showed loading values below 0.70. These indicators originated from the exogenous variables—specifically FERP3, PBAI2, PBAI8, and PBAI10—as well as from the endogenous variables OMI2 and OMI10. However, these indicators recorded only slightly lower loading values and still met other criteria for convergent validity, as demonstrated by factor loadings ≥ 0.70 and AVE values ≥ 0.50. According to Hair et al. (2017, 2022), indicators with loadings between 0.40 and 0.70 may be retained if the construct's Composite Reliability (CR) and AVE continue to meet the required thresholds. Therefore, these indicators remain as analytical parameters in this study. Regarding the assessment of the outer measurement model, these results can be considered acceptable for this research. Table 6 shows that not all conditions for discriminant validity have been fully met, as indicated by the square root of the AVE (Fornell–Larcker criterion) exceeding the correlations between latent components. Furthermore, some constructs demonstrated Composite Reliability and Cronbach's Alpha values ≥ 0.70, while others fell below this threshold.

Table 5. Validity and Reliability Variables

Vrbl_	Indr_	FaLo_	CrAl_	CoRe_	AVE_
AI-Based Forecasting (PBAI)			**0,946**	**0,944**	**0,588**
PBAI1	Mean Absolute Error (MAE) value on demand forecasting model	0,823			
PBAI2	Missing value rate in historical dataset	0,752			
PBAI3	Consistency and integrity level of data used	0,776			
PBAI4	Frequency of forecasting model retraining	0,766			
PBAI5	Responsiveness of model updates to new incoming data	0,855			
PBAI6	Speed of forecasting output update after model retraining	0,771			
PBAI7	Integration level of forecasting system with ERP module	0,825			
PBAI8	System response time in processing data and demand	0,766			
PBAI9	Percentage of system downtime occurrence	0,78			
PBAI10	Mean Absolute Percentage Error (MAPE) value on demand forecasting model	0,726			
PBAI11	Root Mean Square Error (RMSE) value on demand forecasting model	0,864			

PBAI12	Amount of historical data used in forecasting process	0,769			
ERP Flexibility (FERP)			**0,919**	**0,932**	**0,58**
FERP1	Number of optional modules in ERP configurable as needed	0,779			
FERP2	Maximum capacity of system users that can be dynamically increased	0,773			
FERP3	Time required to adjust user capacity on the system	0,697			
FERP4	Number of available APIs (Application Programming Interfaces) or open interfaces	0,706			
FERP5	Number of third-party applications integrated with ERP system	0,724			
FERP6	Average time needed to reconfigure system workflow	0,743			
FERP7	Number of workflows modifiable according to operational needs	0,73			
FERP8	Number of customizable dashboard options available for users	0,811			
FERP9	Percentage of menus and functions in system adjustable by users	0,806			
FERP10	Percentage of ERP features customizable by users	0,832			
Big Data (BD)			**0,898**	**0,921**	**0,66**
BD1	Total data volume produced and captured per specific time period	0,795			
BD2	Speed of new data input process into the system	0,783			
BD3	Frequency of data updates used in analysis and reporting	0,816			
BD4	Number and formats of data manageable by the system	0,86			
BD5	Accuracy and cleanliness (data quality) of available data	0,827			
BD6	Benefits of generated data for management decision-making processes	0,789			
Inventory Management Optimization (OMI)			**0,909**	**0,924**	**0,551**
OMI1	Achievement level of Service Level Agreement (SLA) in inventory management	0,884			
OMI2	Inventory Turnover Ratio during a certain period	0,669			
OMI3	Average inventory quantity available in the system	0,707			
OMI4	Difference between physical inventory and system records	0,797			
OMI5	Accuracy level of generated inventory reports	0,846			
OMI6	Total inventory storage cost during observation period	0,776			
OMI7	Cost of inventory handling and ordering	0,806			
OMI8	Lead time from order to receipt of goods	0,688			
OMI9	Inventory replenishment time after order placement	0,733			
OMI10	Number of stockout incidents occurring	0,662			

Vrbl_ = Variabel, Indr_ = Indikator, FaLo_ = Faktor Loading, CrAl_ = Cronbach's Alpha, rhoA_ = rho_A, CoRe_ = Composite Reliability, AVE_ = Average Variance Extracted

Table 6. Fornell-Larcker criteria (Discriminant Validity)

	BD	FERP	OMI	PBAI
BD	0,812			
FERP	0,445	0,761		
OMI	0,205	0,457	0,742	
PBAI	0,606	0,381	0,168	0,767

4.2 Results of the Inner Structural Model

The evaluation criteria for the Inner Model used the R-squared value (coefficient of determination). Based on Table 7, the average R-squared value was less than 0.75, indicating a lack of direct impact of PBAI, FERP, and BD as exogenous variables on the endogenous variable, namely OMI.

Table 7. R-Squares (Determinant Coefficient)

	RSQU_	RSQA_
OMI	0,209	0,188

RSQU_ = R Square, RSQA_ = R Square Adjusted

To determine the significance of the influence between variables at the 5% significance level, the t-statistic (TSta_) must be greater than 1.65 and the p-value (PVal_) must be less than 0.05. Based on the examination of Table 8 and Figure 2, only the hypothesis of FERP → OMI (TSta_ = 4.142) demonstrates a sufficiently significant effect (according to bootstrapping with TSta_ ≥ 1.65 and PVal_ < 0.05), thus this hypothesis is accepted. Meanwhile, the hypotheses PBAI → OMI and BD → OMI both have TSta_ values below 1.65 and PVal_ values above 0.05, with one of the TSta_ values even being negative, leading to the rejection of these two hypotheses.

Table 8. Conclusion of Hypothesis Testing for all research hypotheses

Hipo_	Hipo_Var	PaCo_	OrSa_	SDD_	TSta_	PVal_	HiTe_
Hipo_1:	PBAI -> OMI	0,007	0,007	0,154	0,047	**0,962**	N_Acpt
Hipo_2:	FERP -> OMI	0,458	0,458	0,111	4,142	**0,000**	Acpt_
Hipo_3:	BD -> OMI	-0,011	-0,011	0,214	0,051	**0,960**	N_Acpt

Hipo_ = Hypotesis, PaCo_ = Path Coefficients, OrSa_ = Original Sample, SDD_ = Standard Deviation, Tsta_ = T Statistics, Pval_ = P Value, Hite_ = Hypothesis, N_Acpt = Not Accepted, Acpt_ = Accepted

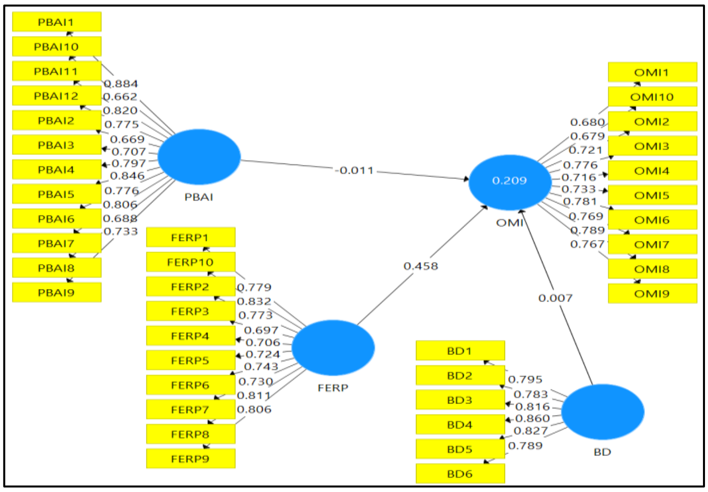

Figure 2. Model summary from Bootstrapping results: Path coefficients, Factor Loadings, and T-values

Based on Figure 2 above, the highest indicator for FERP is FERP10, which represents the Percentage of ERP features that can be customized by users. This indicator measures the proportion of features within the Enterprise Resource Planning (ERP) system that can be independently modified, adjusted, or configured by end-users according to the operational needs of the company. Such customization includes configuring modules, workflows, reports, dashboards, and business rules without having to rely entirely on the ERP vendor for every minor adjustment. This flexibility, supported by a robust system and an intuitive user interface, can significantly enhance the adaptability and effectiveness of inventory management.

The lowest indicator value for the PBAI variable is PBAI10, which refers to the Mean Absolute Percentage Error (MAPE) value in the demand forecasting model. The MAPE indicator measures the average absolute percentage error between actual demand values and forecasted results. It is generally influenced by the quality of historical data, the forecasting methods applied, and the frequency of model updates. However, when the MAPE value is high, it actually indicates a low level of forecasting accuracy, which can hinder inventory management optimization by causing procurement and inventory control decisions to be misaligned with actual needs.

Furthermore, the lowest indicator for the BD variable is BD2, which denotes the Speed of new data input processing into the system. This indicator measures how quickly new data can be entered and processed within the inventory management system. It is generally supported by technological infrastructure, a responsive user interface, and operator competency. However, if the input speed is high but the data quality is poor or unverified, it will not improve inventory management optimization and may instead lead to information errors, inaccurate stock calculations, and discrepancies between system data and actual conditions.

The findings of this study indicate that among the three integrated digital transformation variables examined—Artificial Intelligence (AI)-based forecasting, Enterprise Resource Planning (ERP) flexibility, and Big Data—only ERP flexibility has a significant influence on the optimization of inventory management in the aircraft Maintenance, Repair, and Overhaul (MRO) industry in Indonesia. This result supports prior literature by Pradata and Ernawati (2024), who emphasize the importance of ERP flexibility in positively impacting inventory management performance. However, the AI-based forecasting variable did not show any significant effect, which is presumed to be due to the limited practical implementation of this technology in the field. This aligns with the findings of Wahedi et al. (2023), who revealed that SMEs in the MRO sector generally face obstacles in fully integrating AI, often relying only on partial adoption and remaining dependent on conventional decision-making processes. Additionally, the Big Data variable did not demonstrate any significant effect on inventory management optimization, as its implementation still requires organizational readiness and thorough evaluation to ensure its effectiveness and sustainability (Putra & Arifin, 2021).

For future research, it is recommended to replace the two variables that did not meet the hypotheses in this study—namely AI-based forecasting and Big Data. Subsequent studies may consider substituting these variables with other relevant factors, such as enhanced training, human resource development, leadership, the adoption of AI tools, or by adding or modifying the existing indicators. This would enable the development of new hypotheses that could provide a more significant impact on inventory management optimization in the future.

CONCLUSION

This study concludes that amidst the growing demand for inventory management optimization in Indonesia's aircraft MRO industry, the implementation of digital transformation plays a crucial role but requires a well-directed approach. Based on the quantitative analysis conducted using SmartPLS, only ERP flexibility was found to have a significant influence on enhancing the effectiveness of inventory control, while AI-based forecasting and Big Data did not demonstrate a significant impact. These results emphasize that the feature of ERP systems allowing user customization is the strongest indicator within the ERP flexibility variable in contributing to inventory management optimization. In contrast, the Mean Absolute Percentage Error (MAPE) value in the demand forecasting model under the AI-based forecasting variable and the speed of new data input processing in the Big Data variable were identified as the weakest indicators, showing no significant contribution to inventory management optimization.

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