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The Effects of Routine Maintenance and Engineer Competence on Aircraft Readiness in an Indonesian Flight Operator

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A B S T R A C T

Airlines in Indonesia play a crucial role in air transportation activities, connecting communities across different regions. This research aims to identify one of the root causes of flight delays in an Indonesian airline by examining the influence of routine maintenance and engineer competence on aircraft readiness. The theory utilized in this research is Multivariate Statistics, notably the Structural Equation Model - Partial Least Squares (SEM-PLS) method, employed using questionnaire survey data and internal company data, specifically the annual flight delay data. The research findings show that there is a direct influence of routine maintenance schedule on aircraft readiness by 39.70%; there is a direct influence of spare parts availability on aircraft readiness by 27.60%; there is an indirect influence of routine maintenance schedule and spare parts availability on aircraft availability by 11.30%; and there is an indirect influence of engineer competence and spare parts availability on aircraft availability by 7.30%. The hypothesis stating a significant relationship between engineer competence and aircraft readiness was rejected because, in reality, an engineer's competence would not impact the assistance of adequate equipment and spare parts availability.

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1. INTRODUCTION

Indonesia is an archipelagos country with more than 17,000 islands and with a population of over 270 million people. Therefore, air transportation ensures connectivity and mobility between islands (Gozali, 2022). High aircraft availability facilitates the execution of flight schedules in a timely and efficient manner. That was paramount in the highly competitive aviation industry, where delays can substantially impact an airline's reputation and financial status (Żyluk et al., 2022). This study was conducted on one of the local airlines in Indonesia. According to the report published by the Indonesian Ministry of Air Transportation in 2021, it stated that the Lion group dominated delays in domestic route flights, including PT Batik Air Indonesia accounting for 10% of delays, PT Lion Mentari Airlines with 33%, and PT Wings Abadi Airlines with 36%. That is far from the company's target of limiting flight delays to 5%. The internal audit revealed numerous issues causing these delays, including aircraft availability, a key performance indicator (KPI) in the maintenance department, identified as a contributing factor. Based on the observed phenomena, it is necessary to research the influence of routine maintenance and engineer competency on aircraft readiness within an airline.

2. LITERATURE REVIEW

Structural Equation Modeling (SEM) is a multivariate analysis technique developed to address the limitations of previous analysis models widely used in statistical research (Sarjono & Julianita, 2015). The preferred models include regression analysis, path analysis, and confirmatory factor analysis (Hox & Bechger, 1999). Partial Least Squares (PLS) is a powerful method for analysis due to its minimal dependence on measurement scales (measurements requiring interval or ratio scales), sample size, and distribution of residuals. Indicators in PLS can construct in either reflective or formative types (Sarstedt et al., 2017).

The structural model of the relationship between independent latent variables (exogenous) and latent dependent variables (endogenous) can be represented by the following equation (Chin, 1998):

$$\eta = B\eta + \Gamma\xi + \zeta \quad (1)$$

where,

η (eta) : Vector of random endogenous latent variables of size m.1

ξ (xi) : Vector of random exogenous latent variables of size n.1

B : Coefficient matrix of endogenous latent variables of size m.m

Γ : Coefficient matrix of exogenous latent variables, indicating the relationship of ξ to η of size m.n

ζ(zeta): Vector of random error of size m.1

The assumptions of the latent variable structural equation model used include the following:

a. $E(\eta) = 0$,

b. $E(\xi) = 0$,

c. $E(\zeta) = 0$,

d. ζ is uncorrelated with ξ, and (I - B) is a nonsingular matrix.

The measurement model is part of a structural equation model that describes the relationship between latent variables and their indicators, which is generally modeled as follows:

$$y_{(p.l)} = \Lambda_{y_{(p.m)}}\eta_{(m.l)} + \varepsilon_{(p.l)} \quad (2)$$

$$y_{(q.l)} = \Lambda_{x_{(q.m)}}\xi_{(n.l)} + \delta_{(p.l)} \quad (3)$$

where,

Λ_y : loading matrix between endogenous variables and their indicators.

Λ_x : loading matrix between exogenous variables and their indicators.

ε : measurement error vector of endogenous variable indicators.

δ : measurement error vector of exogenous variable indicators.

p : number of endogenous latent variables.

q : number of exogenous latent variables.

m : number of endogenous variable indicators.

n : number of exogenous variable indicators.

The measurement model equations discussed above (equations 2 and 3) have the following assumptions (Hair et al., 2013):

a. $E(\varepsilon) = E(\delta) = 0$,

b. ε is uncorrelated with η, ξ, and δ,

c. δ is uncorrelated with η, ξ, and ε.

In addition, weight relations connect the inner and outer models to form estimates of exogenous and endogenous latent variables. Case values for each latent variable are estimated in PLS as follows (Gentle et al., 2010):

$$\hat{\xi} = \sum\nolimits_{k} w_{kb} \, . \, x_{kb} \qquad (4)$$

$$\hat{\eta} = \sum\nolimits_{k} w_{ki} . \, y_{ki} \qquad (5)$$

Where w_{kb} and w_{ki} are the kth weights used to estimate the latent variable $\hat{\xi}_b$ and the latent variable $\hat{\eta}_i$, the parameter estimation method used in PLS is Ordinary Least Square (OLS).

The evaluation of the model in PLS consists of two stages: the evaluation of the measurement model and the evaluation of the structural model (Hair et al., 2013). The evaluation of the measurement model can be done using the following criteria (Gentle et al., 2010):

a. Indicator reliability

Indicator reliability indicates the amount of variance in the indicators that can be explained by the latent variable, considering the loading values. If the loading value is less than 0.4, the indicator should be eliminated from the model.

b. Internal consistency/ Construct reliability

Something that can be calculated through the value of composite reliability ($\hat{\rho}$) is more significant than 0.6 using the following equation:

$$\hat{\rho} = \frac{\left(\sum_{i=n}^{n} \hat{\lambda}_i\right)^2}{\left(\sum_{i=1}^{n} \hat{\lambda}_i\right)^2 + \sum_{i=1}^{n} var(\hat{\varepsilon}_i)} \qquad (6)$$

c. Convergent validity

Convergent validity is generally assessed using Average Variance Extracted (AVE) with a minimum of 0.5 to indicate good convergent validity. The calculation of AVE is done using the following equation:

$$AVE = \frac{\sum_{i=1}^{n} \hat{\lambda}_i^{\,2}}{\sum_{i=1}^{n} \hat{\lambda}_i^{\,2} + \sum_{i=1}^{n} var(\hat{\varepsilon}_i)} \qquad (7)$$

d. Discriminant validity

Discriminant validity is evaluated by comparing the square root of AVE values, which should be higher than the correlations between constructs, or AVE values should be higher than the squared correlations between each construct.

To evaluate the structural model, the following criteria can be used (Gujarati, 2003):

a. R square (R^2)

R square represents the percentage of variance explained by the endogenous latent variable using the following equation:

$$R^2 = \sum_{h=1}^{H} \hat{\beta}_{jh} cor\left(X_{jh}, Y_j\right) \qquad (8)$$

b. Path coefficient,

The path coefficient depicts the strength of the relationship between constructs.

c. Effect size (f^2)

The effect size indicates whether the endogenous latent variable has a substantial influence on the exogenous latent variable, calculated using the following equation:

$$f^2 = \frac{R^2{}_{include} - R^2{}_{exclude}}{1 - R^2{}_{include}} \qquad (9)$$

where,

$R^2_{include}$: R^2 calculated involving the exogenous latent variable.

$R^2_{exclude}$: R^2 calculated without involving the exogenous latent variable.

f^2 : 0,02 (weak effect of the exogenous latent variable)

f^2 : 0,15 (moderate effect of the exogenous latent variable)

f^2 : 0,35 (strong effect of the

exogenous latent variable)

d. Stone Geisser (Q^2)

The Stone Geisser value indicates the model's predictive capability if it is above 0 (zero). The Stone Geisser value can be determined using the following equation:

$$Q^2 = 1 - (1 - R^2) \quad (10)$$

e. Goodness of Fit (GoF) Indeks

GoF is used to evaluate the overall structural and measurement model, which can be calculated using the formula equation below:

$$GoF = \sqrt{\overline{communality} \times \bar{R}^2} \quad (11)$$

Where commonalities values obtained by squaring the loading values using the criteria of 0.1 (GoF small), 0.25 (GoF moderate), and 0.36 (GoF significant).

The bootstrapping method has been developed to help reduce the unreliability associated with the misuse of normal distribution and its utilization (Efron, 1979). Bootstrap generates pseudo data (shadow data) by utilizing information and properties from the original data, resulting in shadow data that possess similar characteristics to the original data. In the bootstrap method, sampling is performed with replacement from the data sample (resampling with replacement).

Hypothesis testing (γ and λ) is conducted using the Resampling Bootstrap Method with a minimum of 5000 resamples, and the number of cases must be equal to the number of observations in the original (actual) sample (Efron & Tibshirani, 1993). The hypotheses used are as follows:

a. The statistical hypotheses in the inner model include:

$H_0 : \gamma_i = 0$ (The exogenous variable i is not significant)

$H_0 : \gamma_i \neq 0$ (The exogenous variable i is significant)

b. The hypotheses for the outer model include:

$H_0 : \lambda_i = 0$ (Indicator *i* is not significant)

$H_0 : \lambda_i \neq 0$ (Indicator *i* is significant)

$$t = \frac{\hat{\gamma}}{SE(\hat{\gamma})} \quad (12)$$

or,

$$t = \frac{\hat{\lambda}}{SE(\hat{\lambda})} \quad (13)$$

Suppose the *t* statistic obtained is greater than the critical value *z* at a 2-tailed test, such as 1.65 (at a

Table 1. Previos literature review

No.	Researcher	Title
1	Khair et al. (2022)	The Effect of Training and Organizational Culture on Employee Performance Mediated by Work Discipline in the Electronic Facility & IT Division PT. Angkasa Pura II (Persero) Kantor Cabang Bandara Internasional Kualanamu.
2	Utomo et al. (2022)	Effect of Seniority, Work Experience, and Competence on Promotion of Airport Maintenance Division Employees PT. Angkasapura II (Persero)Bandara Internasional Kuala Namu.
3	Chan et al. (2022)	The Influence Of Service Quality And Corporate Image Of Royal Brunei Airlines: A Partial Least Square Approach.
4	Singh (2015)	Modeling passenger's future behavioral intentions in the airline industry using SEM.
5	Farooq et al. (2018)	Impact of service quality on customer satisfaction in Malaysia Airlines: A PLS-SEM approach

significance level of 10%), 1.96 (at a significance level of 5%), and 2.58 (at a significance level of 1%). In that case, it can conclude that the path coefficient is significant and vice versa (Hair et al., 2011).

Maintenance is a combination of actions to keep an item in or restore it to an acceptable condition (Corder, 1992). Industrial maintenance management is organizing activities to maintain the continuity of a manufacturing or service production system (Kurniawan, 2018).

Based on the search conducted using Harzing's Publish or Perish application, no study with the same title was found in Indonesia. The researcher only found a few variables that are related to the research, and these variables were identified in the following studies (Table 1).

3. RESEARCH METHOD

The type of research conducted can be categorized as a case study, which is an in-depth investigation of an individual, a group, an organization, a program, or the like within a specific time frame (Yin, 2018b). Its purpose is to obtain a comprehensive and profound description of an entity. Case studies generate data that are subsequently analyzed to generate theory.

The data and information collected in this study consist of two parts, which are:

a. Primary Data
   The primary data was obtained from a survey conducted through the distribution of questionnaires to several employees in the maintenance division of Lion Group (Table 2).
b. Secondary Data
   The secondary data was obtained from the internal records of the company and the Ministry of Transportation of Indonesia.

This research needs relevant data to formulate the problem and solve the researched issues (Creswell, 2014). The data collection technique used includes:

a. Documentation
   Documentation is used to obtain data on the dependent variable. In this case, documentation refers to the readiness of the aircraft.
b. Questionnaire
   The questionnaire is a data collection method that provides questions about routine maintenance, engineer competency, and spare part availability to respondents for them to answer.

A sample is a subset of the total number and characteristics of the population (Sugiyono, 2017). The sample can also be a part or representative of the studied population. The sampling in this research was conducted using an incidental sampling technique (Yin, 2018a). The

Table 2. Research questionnaire design

Variables		Questions
Engineer Competence (X1)	X1.1	How long have you been working in this company?
	X1.2	Does my previous work experience relate to my current job?
	X1.3	What is your highest level of education?
	X1.4	I understand the assigned tasks sufficiently.
	X1.5	The problems/troubleshooting align well with the manual book or training I have received
	X1.6	How many training sessions have you attended?
Spare Part Availability (X2)	X2.1	The current lifespan of available spare parts is appropriate.
	X2.4	I assess the quality of frequently replaced spare parts following the standards.
	X2.2	The current waiting time for spare part orders is relatively fast.
	X2.3	The current spare part request procedure is straightforward.
	X2.5	The spare parts are located within the working area.
	X2.6	I find it easy to obtain tools and spare parts while working
Routine Maintenance (X3)	X3.1	Aircraft inspections are conducted regularly as per the predetermined schedule.
	X3.2	The spare part replacement process is in line with the planner's schedule.
	X3.3	The current schedule maintenance work is progressing as per the schedule.
	X3.4	The current maintenance work schedule is carried out with an ideal quantity.
	X3.5	I often witness aircraft flighting in an airworthy condition.
Aircraft	Y1.1	I have never seen flight delays due to unfinished repair processes.

incidental sampling technique can refer to as a sampling method based on chance, where anyone who encounters the researcher can be used for sampling if they are considered suitable as a data source (Ghozali, 2021).

The calculation results determined that the number of samples to take is 242.21 individuals, rounded up to 243 individuals. This sample size is the target that must be achieved by the researcher in order to accomplish the research objectives. In this study, the questionnaire was designed according to the variables being investigated based on the sources of books and journals collected. The details of the question design in the questionnaire are as Table 2.

The measurement scale used in this study is the Likert scale. The Likert scale is used to measure the attitudes, opinions, and perceptions of an individual or a group of people toward a social event/phenomenon (Sugiyono, 2017). The Likert scale used in this research includes responses in the form of numbers from one to five, namely: 1 = Strongly Disagree (SD); 2 = Disagree (D); 3 = Neutral (N); 4 = Agree (A); 5 = Strongly Agree (SA).

The data analysis technique used in this study to analyze the influence of routine maintenance and engineer competence on aircraft readiness through the intervening variable of spare part availability is:

a. Descriptive Analysis.
   This method is used to present quantitatively descriptive data on the variables in this study, which include routine maintenance, engineer competence, spare part availability, and aircraft readiness. These variables consist of several highly supportive indicators, further developed into instruments (questionnaires).

b. Analysis Assumptions Testing.
   The purpose of conducting analysis assumptions testing is to determine the validity of the research hypothesis. After the data is collected, it undergoes data processing to conclude.

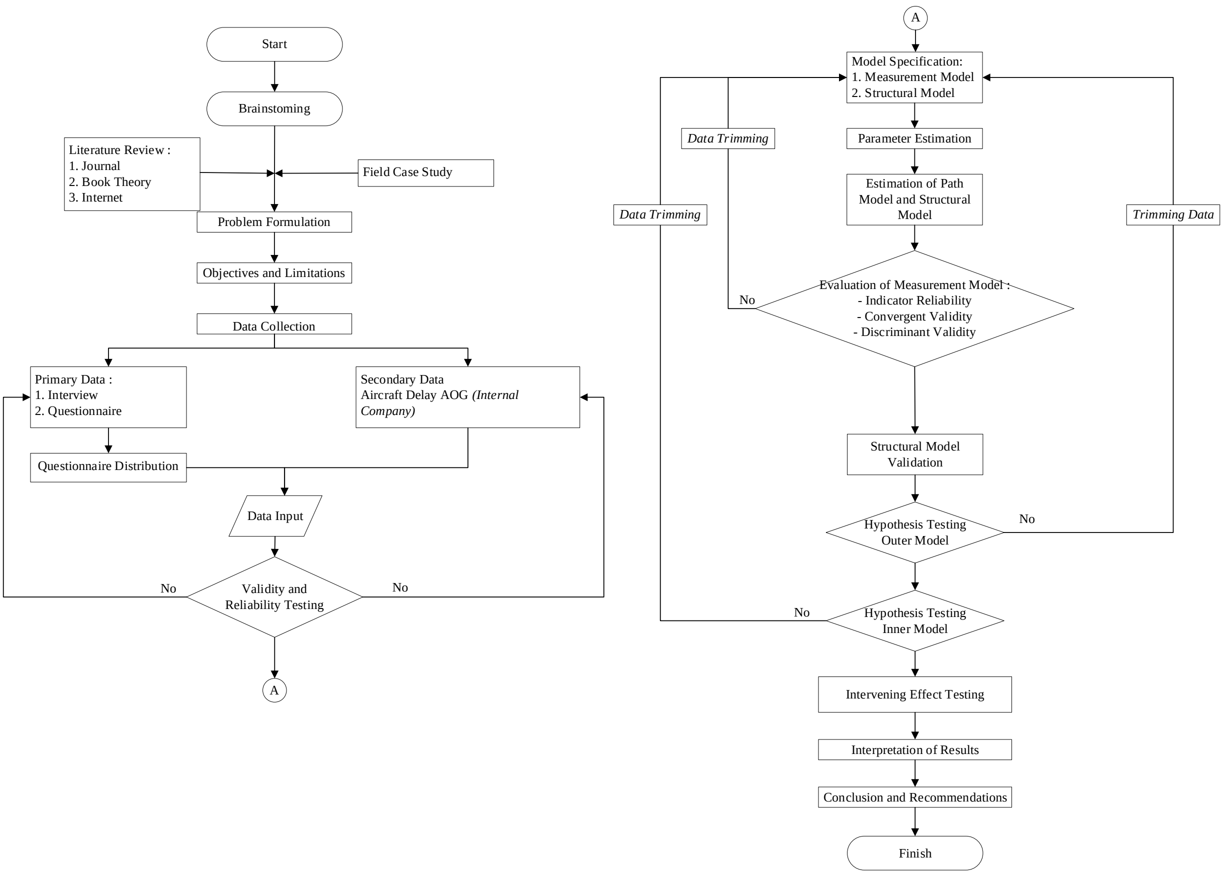

Figure 1. Research flow diagram

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b. Analysis Assumptions Testing.
   The purpose of conducting analysis assumptions testing is to determine the validity of the research hypothesis. After the data is collected, it undergoes data processing to conclude.

The steps taken in the research to achieve the desired objectives include several stages, as shown in Figure 1.

4. RESULT AND DISCUSSION

This research is based on the responses from respondents in the maintenance division of Lion Group at Soekarno Hatta Airport. The detailed description of the respondents who answered the questionnaire can be seen in Table 3.

Table 3 shows that the number of questionnaires that received responses is 251 individuals (83.67%) out of 300 individuals who were sent the questionnaire. The number of responses aligns with the target sample, which should have been 243 individuals.

The competence variable of engineers, based on the educational background indicator of high school/vocational school, holds the highest percentage at 68.53%. The highest percentage of work experience falls under the 8-11 years category, accounting for 60.56%. Furthermore, training and development programs have been conducted more than 14 times, representing 62.95%. Based on these indicators, the competence of engineers is in relatively good condition.

Measurement model evaluation is conducted first to verify the indicators and latent variables before hypothesis testing to predict the relationships between latent variables in the structural model. Indicator reliability indicates how much variance of the latent variable can be explained by the indicators. In indicator reliability, a reflective indicator should be removed (eliminated) from the measurement model when the loading value (λ) is less than 0.4. The loading values (λ) obtained can be seen in Figure 2.

Based on Figure 2, it can be observed that indicators X1.1, X1.2, X1.3, X1.6, X2.5, X3.4, and Y1.2 should be eliminated as they have loading factor (λ) values below 0.4. After the elimination process, the results can be seen in Figure 3. The following criterion examines

Table 3. Respondent description

Criteria	Category	Frequency	Percentage
Sample	Received	251	83,67%
	Distributed	300	
Highest Education Level	High School	172	68,53%
	Diploma	52	20,72%
	Bachelor's Degree	27	10,76%
Work Experience	4 - 7 years	51	20,32%
	8 - 11 years	152	60,56%
	12 - 15 years	39	15,54%
	> 16 years	9	3,59%
Training	2 - 5 times	13	5,18%
	6 - 9 times	30	11,95%
	10 - 13 times	50	19,92%
	> 14 times	158	62,95%

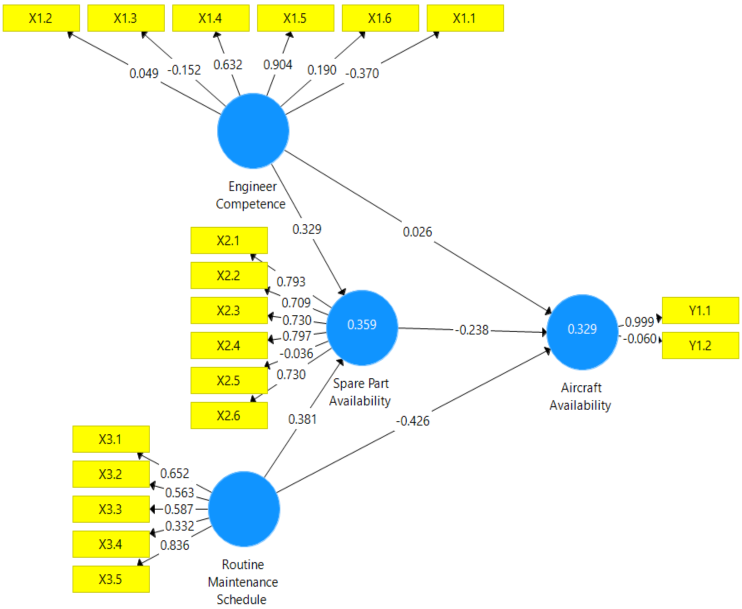

Figure 2. Loading PLS algorithm 1#

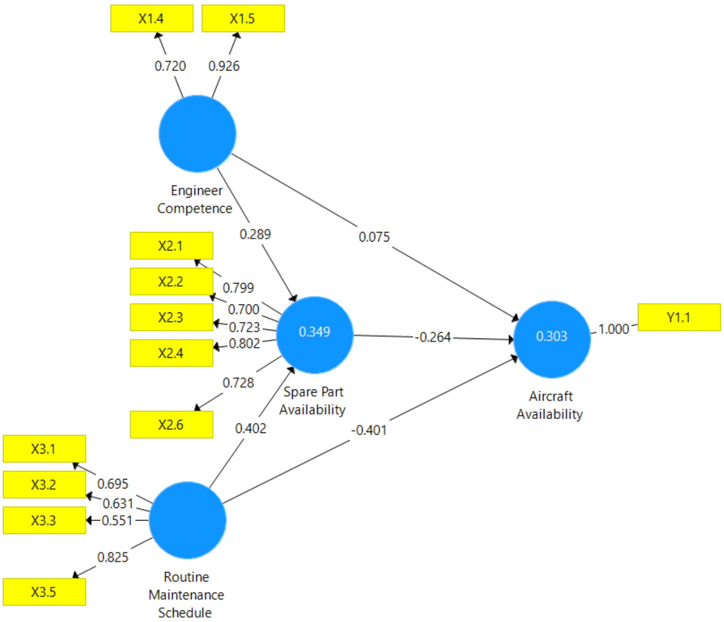

Figure 3. Loading PLS Algorithm 2#

Table 4. Composite reliability and AVE values of measurement model 1#

Variable	Composite Reliability	Average Variance Extracted *(AVE)*
Aircraft Availability (Y1)	1,000	1,000
Spare Part Availability (X2)	0,866	0,565
Engineer Competence (X1)	0,813	0,688
Routine Maintenance Schedule (X3)	0,774	0,466

composite reliability and convergent validity (AVE). Table 4 shows that four variables have composite reliability values above 0.6, indicating that the established indicators can effectively measure each latent variable (construct) or, in other words, the four measurement models are reliable.

values shown in Table 4 reveal variables with a value of 0.466 (below 0.5), indicating insufficient convergent validity or not meeting the convergent validity criteria. To achieve the required AVE value, further elimination of indicators below 0.6

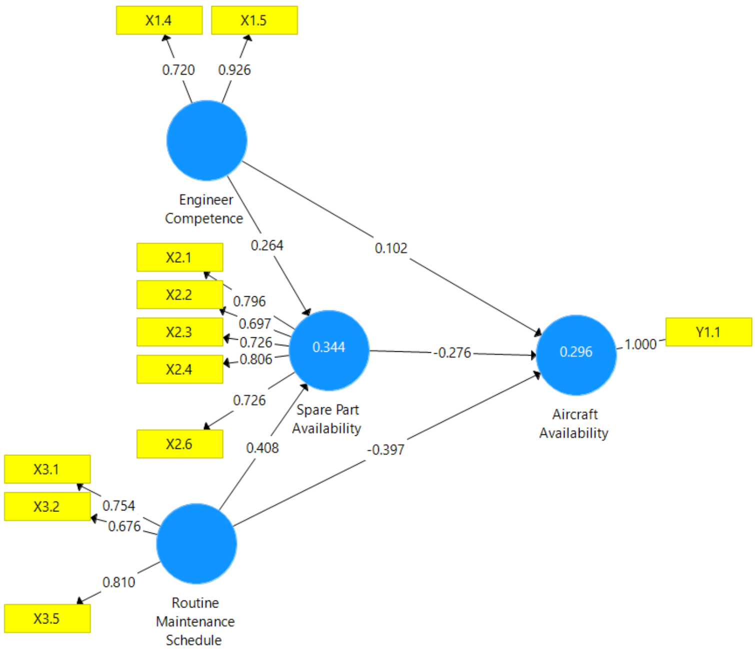

Figure 4. Loading PLS Algorithm 3#

Table 5. Composite reliability and AVE values of measurement model 2#

Variable	(Y1)	(X2)	(X1)	(X3)
Aircraft Availability (Y1)	**1,000**			
Spare Part Availability (X2)	-0,443	**0,751**		
Engineer Competence (X1)	-0,228	0,469	**0,829**	
Routine Maintenance Schedule (X3)	-0,496	0,540	0,504	**0,749**

Good convergent validity is indicated by higher correlations among the indicators that comprise a construct. The AVE (Average Variance Extracted)

is conducted for the routine maintenance schedule, specifically for indicator X3.3 (Figure 3).

In Figure 4, the loading values (λ) obtained after

Table 6. Correlations between latent variables

Variable	Composite Reliability	Average Variance Extracted (AVE)
Aircraft Availability (Y1)	1,000	1,000
Spare Part Availability (X2)	0,866	0,564
Engineer Competence (X1)	0,813	0,688
Routine Maintenance Schedule (X3)	0,792	0,560

eliminating indicator X3.3 can be observed. In this model, the lowest loading value is 67.60% (indicator X3.2), and overall, each latent variable has successfully explained the variance of its measuring indicators at values above 60%.

Further iterations were performed by re-examining the composite reliability and convergent validity (AVE) after conducting the third PLS Algorithm (Figure 4). In Table 5, the results show composite reliability values above 0.6 and Average Variance Extracted (AVE) values above 0.5, indicating that the measure of convergent validity is appropriate and meets the criteria for convergent validity. The next step is to examine the Discriminant Validity criteria by comparing the correlations between constructs with the Average Variance Extracted (AVE) square root, as shown in Table 6. Based on the data in the table, it can be observed that the square root of AVE is higher than the correlation values between latent variables, or it can be simplified through the presentation in Table 7. After completing the measurement model evaluation, several equations are derived, as shown below:

a. $X_{1.4}$ = 0,720 Engineer Competence + $\delta_{1.4}$
b. $X_{1.5}$ = 0,926 Engineer Competence + $\delta_{1.5}$
c. $X_{2.1}$ = 0,796 Spare Part Availability + $\delta_{2.1}$
d. $X_{2.2}$ = 0,697 Spare Part Availability + $\delta_{2.2}$
e. $X_{2.3}$ = 0,726 Spare Part Availability + $\delta_{2.3}$
f. $X_{2.4}$ = 0,806 Spare Part Availability + $\delta_{2.4}$
g. $X_{2.6}$ = 0,726 Spare Part Availability + $\delta_{2.6}$
h. $X_{3.1}$ = 0,754 Routine Maintenance Schedule + $\delta_{3.1}$
i. $X_{3.2}$ = 0,676 Routine Maintenance Schedule + $\delta_{3.2}$
j. $X_{3.5}$ = 0,810 Routine Maintenance Schedule + $\delta_{3.5}$
k. $Y_{1.1}$ = Aircraft Availability

Based on the equations above, the minor contribution is the prevalence of spare part replacement process time ($X_{3.2}$), while the most significant contribution is the proportion of problem/troubleshooting suitability ($X_{1.5}$). The bootstrapping process with a sample size 251 for resampling and 5000 iterations at a significance level of 5% produces path coefficients and t-statistic values, as shown in Table 8.

Table 7. The square root of AVE values and discriminant validity for each latent variable

Variable	The square	Discriminant Validity
Aircraft Availability (Y1)	1,000	Accepted
Spare Part Availability (X2)	0,751	Accepted
Engineer Competence (X1)	0,829	Accepted
Routine Maintenance Schedule (X3)	0,748	Accepted

Table 8. The path coefficient values of the structural model

Item	Standard Deviation	T Statistics	P-Values
Spare Part Availability (X2) -> Aircraft Availability (Y1)	0,089	3,123	0,002*
Engineer Competence (X1) -> Aircraft Availability(Y1)	0,064	1,586	0,113*
Engineer Competence (X1) -> Spare Part Availability (X2)	0,062	4,257	0,000*
Routine Maintenance Schedule (X3) -> Aircraft Availability(Y1)	0,087	4,579	0,000*
Routine Maintenance Schedule (X3) -> Spare Part Availability(X2)	0,068	6,022	0,000*

Table 9. The f-square values of each exogenous latent variable

Item	f-square	Note
Engineer Competence (X1)	0,010	Strong
Engineer Competence (X1) -> Spare Part Availability (X2)	0,079	Moderate
Spare Part Availability (X2)	0.071	Moderate
Routine Maintenance Schedule (X3)	0,141	Moderate
Routine Maintenance Schedule (X3) -> Spare Part Availability (X2)	0,189	Strong

Furthermore, the model's fitness is tested using the R^2 value. The R^2 value for spare part availability is 0.344, and for aircraft availability, it is 0.296. These values explain that the variability of the endogenous variables explained by the variability of the exogenous variables is 34.4% and 29.6%, respectively.

In Table 9, the examination results regarding the influence of endogenous variables on exogenous variables can be observed based on the effect size (f^2) values. From the data in the table, it can be seen that the weakest influence is found in the engineer competence variable, which has a value of 0.01 (below 0.02). In contrast, the most decisive influence is seen in the routine maintenance variable through the spare part availability variable, which has a value of 0.189 (between 0.15 - 0.35).

Based on the Stone Geisser calculations above, it can be observed that the model has the good predictive capability as all the calculations yield values above 0 (zero). The Goodness-of-Fit (GoF) value obtained is 0.558 (large), indicating that the model can explain empirical data. Therefore, overall, the formed model is valid.

To simplify calculations, the model can be represented by the following equations:

Y1=0,102 X1-0,397 X3-0,113 X2.X3-0,073 X1.X2+ζ

Based on the equations above, it can be interpreted that aircraft readiness is a measurement tool used by the maintenance division in Lion Group, which is influenced by engineer competence, routine maintenance schedule, and spare part availability. Hypothesis testing is conducted using Smart PLS software based on the direct and indirect path coefficient values obtained from the bootstrapping process (Table 10).

Based on the data in the table, the results of the proposed hypotheses are as follows:

a. H_1 : There is a significant influence between routine maintenance and aircraft readiness.
Based on the analysis in Table 9, it can be stated that H1 is accepted and H0 is rejected because the p-value is smaller than the t-statistic value. According to Figure 5, the influence of routine maintenance on aircraft readiness is 39.70%

b. H_2 : There is a significant influence between routine maintenance and spare part availability on aircraft readiness.
Based on the analysis in Table 9, it can be stated that H1 is accepted and H0 is rejected because the p-value is smaller than the t-statistic value. According to Figure 5, routine maintenance through spare part availability influences aircraft readiness by 11.30% (a result of 0.408 x 0.276).

c. H_3 : There is a significant influence between spare part availability and aircraft readiness .
Based on the analysis in Table 9, it can be stated that H1 is accepted and H0 is

Table 10. Path coefficient values of the hypothesis influence

Variabel	Standard Deviation	T Statistics	P-Values
Routine Maintenance Schedule (X3) -> Aircraft Availability (Y1)	0,072	7,117	0,000
Routine Maintenance Schedule (X3) -> Spare Part Availability (X2) -> Aircraft Availability (Y1)	0,045	2,501	0,012
Spare Part Availability (X2) -> Aircraft Availability (Y1)	0,089	3,123	0,002
Engineer Competence (X1) -> Aircraft Availability (Y1)	0,062	0,468	0,640
Engineer Competence (X1) -> Spare Part Availability (X2) -> Aircraft Availability (Y1)	0,024	3,013	0,003

rejected because the p-value is smaller than the t-statistic value. According to Figure 5, the influence of spare part availability on aircraft readiness is 27.60%.

d. H_4 : There is a significant influence between engineer competence and aircraft readiness.
Based on the analysis in Table 9, it can be stated that H1 is rejected and H0 is accepted because the p-value is greater than the t-statistic value. According to Figure 5, the influence of engineer competence on aircraft readiness is 10.20%.

e. H_5 : There is a significant influence between engineer competence and spare part availability on aircraft readiness.
Based on the analysis in Table 9, it can be stated that H1 is accepted and H0 is rejected because the p-value is smaller than the t-statistic value. According to Figure 5, the influence of engineer competence through spare part availability on aircraft readiness is 7.30% (result of 0.264 x 0.276).

Based on the discussion above, the following alternative improvements can be offered to the company:

a. Optimal scheduling improvement through problem/troubleshooting alignment mitigation. In this aspect, a review can be conducted starting from managing Root Cause Analysis to identify and inventory the occurring problems and find optimal alternative solutions. This will enable the development of engineer SOPs and serve as a reference for future personnel planning.

b. Preparation and mapping of equipment and spare part needs.
Preparation and mapping of equipment and spare parts needed in the future can be synchronized to expedite the work process of the engineers in the field.

c. It enhances the involvement of engineers in equipment and spare part needs.
This activity is crucial to ensure that engineers perform routine and incidental maintenance tasks more efficiently and accurately. There should be no work that cannot be completed due to waiting for unavailable spare parts and equipment.

5. CONCLUSION

Based on the research findings, it can be concluded that there is a direct influence of routine maintenance schedule on aircraft readiness by 39.70%; there is a direct influence of spare part availability on aircraft readiness by 27.60%; there is an indirect influence of routine maintenance schedule and spare part availability on aircraft availability by 11.30%; and there is an indirect influence of engineer competence and spare part availability on aircraft availability by 7.30%.

Based on the data analysis results, the hypothesis stating a significant relationship between engineer competence and aircraft readiness is rejected. This is reasonable because an engineer's competence alone would only have an impact with the assistance of adequate tools and spare parts availability in addressing issues.

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