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Analysis of Strategic Cooperation Between PT. Pindad and MBDA (Matra Bae Dynamics Alenia) in Building Competitive Advantage for the Production of the Mistral Atlas Platform

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ABSTRACT

This research aims to analyze the strategic cooperation between PT. Pindad, an Indonesian defense company, and MBDA (Matra Bae Dynamics Alenia), a leading missile systems company from France, in the development and production of the Mistral Atlas platform. This cooperation represents a crucial step in enhancing Indonesia's national defense capacity, particularly in addressing increasingly complex aerial threats. The research examines the collaboration process, technical challenges encountered, and the impact of this partnership on product innovation, competitive advantage, and company performance. The results of Structural Equation Modelling (SEM) analysis indicate that the strategic alliance between PT. Pindad and MBDA has a significant positive impact on enhancing product innovation, as manifested in product value. This alliance not only improves PT. Pindad's employees' skills through technology transfer but also contributes to greater product differentiation, which directly strengthens the company's competitive advantage. Product differentiation, in turn, has a significant impact on PT. Pindad's financial performance, thereby boosting the company's competitiveness in the global defense industry market. This research identifies key factors influencing the success of this strategic cooperation, including alliance quality, goal alignment, and employee skills. Based on these findings, the research provides recommendations for further development in the defense industry, particularly in enhancing product innovation and strengthening competitiveness through effective strategic collaboration. Thus, this research is expected to contribute significantly to understanding strategic cooperation in the defense industry and to support efforts to increase Indonesia's defense self-reliance.

KEYWORDS *strategic analysis, product innovation, competitive advantage, defense industry, Structural Equation Modelling (SEM)*

INTRODUCTION

In recent years, the world has witnessed numerous armed conflicts that have impacted not only the directly involved countries but also international stability and security (Scharre, 2018; Singer, 2021; Žižek et al., 2022). Wars in various parts of the world, such as in the Middle East, Eastern Europe, and other regions, remain the main focus of global discussions on peace and security. In addition, the development of military technology and advanced weapons further heightens threats to global security (Brands, 2023; Mearsheimer, 2019).

State defense is a crucial aspect that must be prioritized to ensure the nation's existence and survival (Buzan et al., 2023; Laksmana, 2019). The function of state defense involves protecting sovereignty, territorial integrity, and the safety of all citizens from various threats and disturbances to national unity (Connelly & Bitzinger, 2021; Mietzner, 2020; Salim, 2018). Indonesia faces multidimensional challenges due to its complex geographical characteristics. Law of the Republic of Indonesia Number 34 of 2004 mandates that the TNI, as the main component, is tasked with upholding state sovereignty, maintaining the territorial integrity of the Republic of Indonesia, and protecting the entire nation and all Indonesian blood from threats and disturbances to national integrity. To carry out these main tasks effectively, the TNI must possess strong deterrent capabilities to confront and overcome every form of threat. The Industrial Revolution 4.0 has transformed the paradigm of modern warfare through the integration of advanced technologies such as artificial intelligence, big data, machine learning, automation, and robotics. Warfare is no longer limited to land, sea, and air domains but has extended into space and cyberspace (Sayler, 2020). Cutting-edge technologies such as railguns, hypersonic missiles, directed-energy weapons, and unmanned combat vehicles further broaden the threat spectrum and increase combat complexity (Heidenkamp et al., 2018). Modern warfare is also characterized by concepts such as asymmetric warfare, infinite warfare, and Network Centric Warfare (NCW), which leverage advantages in information technology, communication, and weapons systems (Boulanin & Verbruggen, 2017; Johnson, 2019; Payne, 2021).

In the context of national defense, the TNI must adapt to technological developments. Mastery of defense technology is an absolute necessity to enhance early detection, rapid response, and threat anticipation capabilities. The TNI must evolve into a modern, adaptive institution capable of maintaining high resilience at both regional and global levels. Achieving this requires qualified human resources, adequate training, and reliable modern defense equipment that is highly effective and suited to operational environments (Colby, 2021; Green et al., 2023).

The dynamics of the global and regional strategic environment also shape Indonesia's defense development (Mizokami, 2019).. International conflicts such as Russia-Ukraine and Iran-Israel have demonstrated the use of guided missiles as long-range precision strike tools. In the Asia-Pacific region, China's military modernization and South China Sea claims are fueling geopolitical tensions, prompting the United States to bolster its military presence. The military power of these major countries places Indonesia within range of various modern weapon systems, from strategic bombers and fighter jets to cruise missiles and intercontinental ballistic missiles.

To counter increasingly complex threats, Indonesia needs a modern, layered air defense system. Three main capabilities must be developed: electronic attack, passive defense, and air defense artillery *(arhanud)*. *Arhanud* plays a crucial role in active air defense by neutralizing various aerial threats, such as aircraft, ballistic missiles, and guided missiles. However, much of the TNI AD's *arhanud* equipment consists of outdated products, such as 1950s-era cannons, making modernization urgently necessary to ensure operational readiness and national air defense effectiveness.

To address these challenges, PT Pindad collaborated with the French company MBDA in developing the Mistral Atlas missile platform. MBDA, as a multinational defense firm, possesses superior expertise in missile technology, including air defense and long-range systems. This collaboration facilitates technology transfer, enhances domestic industry capacity, and strengthens national production of defense equipment. PT Pindad, as a strategic state-owned enterprise in the defense sector, gains opportunities through this partnership to bolster its competencies in modern defense equipment development and expand its defense sector capabilities.

This research aims to analyze product innovations from the PT Pindad-MBDA collaboration on the Mistral Atlas platform, evaluate the competitive advantages gained, and examine their impact on PT Pindad's performance. Through validity and hypothesis testing using SPSS and SmartPLS, the study provides a comprehensive assessment of this strategic cooperation's effectiveness. Beyond its theoretical contributions to strategic management literature in the defense industry, the research offers practical recommendations to enhance cooperation effectiveness, production efficiency, and national defense industry independence.

METHOD

This research employed a quantitative verifiable approach utilizing Structural Equation Modeling (SEM) based on Partial Least Squares (PLS) to analyze the effectiveness of strategic cooperation between PT Pindad and MBDA in developing the Mistral Atlas platform. The research design followed a systematic process that began with preliminary studies on rocket launcher technology challenges, followed by a comprehensive literature review on strategic alliances, innovation, competitive advantage, and company performance. The research model was constructed based on theoretical relationships between variables and tested using SEM-PLS to evaluate validity, reliability, and structural relationship strength through outer model analysis, inner model assessment, and hypothesis testing via the bootstrapping method.

The research population comprised all stakeholders directly involved in the PT Pindad-MBDA collaboration, including employees from PT Pindad's research and development division, MBDA technical staff stationed in Indonesia, Ministry of Defense officials overseeing the project, and personnel from *Pussenarhanud* (Indonesian Army Air Defense Artillery Center). Using a purposive sampling technique, 80 respondents were selected based on specific criteria: (1) direct involvement in the Mistral Atlas platform development for a minimum of six months; (2) technical or managerial positions related to the project; and (3) willingness to participate voluntarily. This sample size exceeded the minimum requirement for PLS-SEM analysis, which typically requires 10 times the largest number of structural paths directed at a particular construct (Hair et al., 2017).

Data collection employed mixed methods combining primary and secondary sources. Primary data were gathered through structured questionnaires using a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree) and in-depth interviews with key informants from PT Pindad, MBDA, and government stakeholders. The questionnaire was developed based on established instruments from prior research on strategic alliances, competitive advantage (Barney, 1991), and organizational performance (Kaplan & Norton, 1996), with modifications to suit the defense industry context. Secondary data were obtained from official reports, technical documentation, academic journals, and supporting documents related to the collaboration. Prior to distribution, the questionnaire underwent content validity assessment by three experts in defense management and strategic alliances, followed by pilot testing with 30 respondents to ensure clarity and reliability. The final instrument consisted of 34 items measuring four main constructs: strategic alliance (10 items), product innovation (8 items), competitive advantage (8 items), and company performance (16 items).

Data analysis followed a systematic process: (1) descriptive statistics to profile respondent characteristics and variable distributions; (2) validity testing using Pearson correlation to ensure each item measured the intended construct (valid if $r > 0.254, \alpha = 0.05$); (3) reliability testing using Cronbach's alpha (reliable if $\alpha > 0.60$); (4) factor analysis to identify the underlying factor structure; and (5) SEM-PLS analysis to test hypothesized relationships between constructs. The SEM-PLS approach was selected for its capability to handle complex models with multiple relationships, smaller sample sizes, and non-normal data distributions (Henseler et al., 2015). Model evaluation included outer model assessment (convergent validity, discriminant validity, composite reliability) and inner model assessment (R^2, path coefficients, effect sizes). Hypothesis testing employed a bootstrapping procedure with 5,000 resamples to determine statistical significance ($p < 0.05$).

RESULT AND DISCUSSION

1. Validity and Feasibility Test

Data processing in research is a critical stage that determines the reliability and validity of the results obtained. Without proper data processing, research results can be distorted, which in turn can affect the conclusions drawn. In this context, the validity and reliability test becomes the main foundation that ensures that the research instrument used actually measures the intended concept (validity) and provides consistent results when measurements are made repeatedly (reliability). This process is very important because valid and reliable research results are a prerequisite for drawing conclusions that are trustworthy and useful for the development of theory and practice.

The validity of the instrument in the study refers to the extent to which the instrument is able to measure the expected concept. Hair et al. (2014) state that validity is the essence of a good measurement instrument, because without validity, the results obtained from research can be very misleading. For example, if an instrument is said to have high validity, then it can be ensured that it actually measures what it should be measured, such as customer satisfaction, loyalty, or organizational performance. On the other hand, reliability refers to the consistency of measurements; a reliable instrument will give the same results if used under the same conditions at different times (Creswell, 2013). This reliability is important in social research, where the variables measured often have many factors that can influence the outcome.

1) Testing the Validity and Reliability of Strategic Alliances

The data is declared valid if the correlation coefficient exceeds the table coefficient (r> rtable calculation 0.254) with an error rate of Alpha 0.05 and a significance value of <0.05. The results of the recapitulation of this validity test are shown in table 1 below.

Table 1. Results of the validity test of strategic alliances

Variabel	Indicator	Coeficin	Sig. (2tailed)	Information
Product Value	X1	0,538	<0.001	Valid
	X2	0,537	<0.001	Valid
	X3	0,607	<0.001	Valid
Commercial Value	X4	0,785	<0.001	Valid
	X5	0,389	<0.001	Valid
	X6	0,516	<0.001	Valid
Market Expansion	X7	0,702	<0.001	Valid
	X8	0,722	<0.001	Valid
Employee Skills	X9	0,719	<0.001	Valid
	X10	0,700	<0.001	Valid

(Source: Data Processing Results, 2023)

The results of the validity test shown in the table above show that all question items used in this study have met the validity criteria, making them suitable for use in further analysis. Furthermore, a reliability test is carried out by the researcher to assess the consistency of the data obtained, especially in terms of whether the data will produce similar results if the measurements are made repeatedly. Reliability is declared adequate if the Cronbach's Alpha value obtained is greater than or greater than 0.60, indicating that the instrument used is reliable.

Table 2. Results of the strategic alliance reliability test

Reliability Statistics	
Cronbach's Alpha	N of Items
0,786	10

(Source: Data Processing Results, 2023)

Based on Table 2 above, it can be concluded that the processed data has a Cronbach's Alpha value of 0.786, which is higher than the threshold of 0.60. Therefore, the data shows good consistency if repeated measurements, which means that the data has met the reliability criteria.

2) Competitive Advantage Validity and Reliability Test

The data is declared valid if the correlation coefficient exceeds the table coefficient (r> rtable calculation 0.254) with an error rate of Alpha 0.05 and a significance value of <0.05. The results of the recapitulation of this validity test are shown in table 3 below.

Table 3. Results of the competitive advantage validity test

Variable	Indicator	Coeficin	Sig. (2tailed)	Information
Alliance Quality	X1	0,733	<0.001	Valid
	X2	0,772	<0.001	Valid
Alignment of Purpose	X3	0,648	<0.001	Valid
	X4	0,764	<0.001	Valid
Differentiation	X5	0,532	<0.001	Valid
	X6	0,378	<0.001	Valid
	X7	0,474	<0.001	Valid
	X8	0,451	<0.001	Valid

(Source: Data Processing Results, 2023)

The results of the validity test shown in the table above show that all question items used in this study have met the validity criteria, making them suitable for use in further analysis. Furthermore, a reliability test is carried out by the researcher to assess the consistency of the data obtained, especially in terms of whether the data will produce similar results if the measurements are made repeatedly. Reliability is declared adequate if the Cronbach's Alpha value obtained is greater than or greater than 0.60, indicating that the instrument used is reliable.

Table 4. Competitive Advantage Performance Reliability Test Results

Reliability Statistics	
Cronbach's Alpha	**N of Items**
0,836	8

(Source: Data Processing Results, 2023)

Based on Table 4 above, it can be concluded that the processed data has a Cronbach's Alpha value of 0.836, which is higher than the threshold of 0.60. Therefore, the data shows good consistency if repeated measurements, which means that the data has met the reliability criteria.

3) Testing the Validity and Reliability of Company Performance

The data is declared valid if the correlation coefficient exceeds the table coefficient (r> rtable calculation 0.254) with an error rate of Alpha 0.05 and a significance value of <0.05. The results of the recapitulation of this validity test are shown in table 5 below.

Table 5. Results of the company's performance validity test

Variable	Indicator	Coeficin	Sig. (2tailed)	Information
Financial Performance	X1	0,703	<0.001	Valid
	X2	0,730	<0.001	Valid
Company Productivity	X3	0,499	<0.001	Valid
	X4	0,410	<0.001	Valid
	X5	0,371	<0.001	Valid
	X6	0,582	<0.001	Valid
The growth of PT. São Paulo	X7	0,571	<0.001	Valid
	X8	0,447	<0.001	Valid
	X9	0,532	<0.001	Valid
	X10	0,382	<0.001	Valid
Company Competitiveness	X11	0,475	<0.001	Valid
	X12	0,624	<0.001	Valid
	X13	0,615	<0.001	Valid
Sustainability	X14	0,596	<0.001	Valid
	X15	0,589	<0.001	Valid
	X16	0,537	<0.001	Valid

(Source: Data Processing Results, 2023)

The results of the validity test shown in the table above show that all question items used in this study have met the validity criteria, making them suitable for use in further analysis. Furthermore, a reliability test is carried out by the researcher to assess the consistency of the data obtained, especially in terms of whether the data will produce similar results if the measurements are made repeatedly. Reliability is declared adequate if the Cronbach's Alpha value obtained is greater than or greater than 0.60, indicating that the instrument used is reliable.

Table 6. Results of the company's performance reliability test

Reliability Statistics	
Cronbach's Alpha	**N of Items**
0,794	16

(Source: Data Processing Results, 2023)

Based on Table 6 above, it can be concluded that the processed data has a Cronbach's Alpha value of 0.794, which is higher than the threshold of 0.60. Therefore, the data shows good consistency if repeated measurements, which means that the data has met the reliability criteria.

2. Factor Analysis

Factor analysis is applied to determine the variables that will be used in the research to be carried out. The data analyzed in this factor analysis was obtained from the results of the distribution of questionnaires that had been given to the employees of PT. Pindad, MBDA, the Ministry of Defense, and Pussenarhanud are involved in this collaboration. The following are the steps that have been taken.

a) KMO and Bartlett’s Test

Table 7. Results of factor 1 analysis test

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,834
Bartlett's Test of Sphericity	Approx. Chi-Square	784,529
	df	162
	Sig.	,000

(Source: Data Processing Results, 2024)

If the KMO MSA value is greater than 0.50 and the Bartlett's Test of Sphericity (Sig.) value is less than 0.005, then the factor analysis technique can be continued. Based on the results of the above output, it is known that the KMO MSA value is 0.834 which is greater than 0.50, and the Bartlett's Test of Sphericity (Sig.) value is 0.000 which is less than 0.005. Therefore, factor analysis can be continued because it has met the set criteria.

b) Communalities Table

The Communalities table is used to evaluate the extent to which the variables studied are able to explain the factors formed in the factor analysis. Communality shows the proportion of variance of a variable that can be explained by the factors resulting from the analysis. In this context, the variable is considered to have an adequate contribution in explaining the factor if the extraction value exceeds 0.50. That is, more than 50% of the variance of the variable is explained by the factors that have been extracted.

If the extraction value of a variable is less than 0.50, this indicates that the variable is less able to explain the factor significantly, and may need to be considered for removal or regrouping in further analysis. This Communalities table serves as an important initial evaluation tool to ensure that only those variables with a strong contribution to the factor structure are preserved, thus strengthening the overall validity of the resulting factor model.

Table 8. Results of factor 2 analysis test

Communalities		
	Initial	Extraction
X1	1.000	.694
X2	1.000	.930
X3	1.000	.554
X	1.000	.992
Y1	1.000	.701
Y2	1.000	.886
Y3	1.000	.664
Y	1.000	.986
Z1	1.000	.709
Z2	1.000	.814
Z	1.000	.995
A1	1.000	.780
A2	1.000	.803
A	1.000	.997
Extraction Method: Principal Component Analysis.		

(Source: Data Processing Results, 2024)

Based on the output generated from factor analysis, the entire Extraction value obtained shows a number greater than 0.50. This indicates that each variable analyzed has a strong enough ability to explain the factors that are formed. In other words, the variance captured by each variable in the model is already more than 50%, which means that the variables significantly contribute to the composition of the factors.

Therefore, it can be concluded that all the variables measured meet the eligibility requirements for use in determining factors in the analysis of these factors. There are no variables that need to be excluded or considered for revision, as all of them have been shown to have an adequate contribution. This shows that the model of factors resulting from this analysis is stable and valid, with the entire variable playing an important role in the structure that is formed.

c) Total Variance Explained Table

The Total Variance Explained table is used to provide a complete picture of how the variance of the overall variables being analyzed is distributed among the factors formed through factor analysis. This table consists of several important components that allow researchers to understand the extent to which these factors are able to explain the variability of existing data.

The Initial Eigenvalues table shows the number of initial factors extracted from the data, which is based on the Eigenvalue of each factor. Eigenvalue measures the total number of variances explained by a particular factor; the higher the Eigenvalue, the greater the contribution of these factors in explaining the variance in the dataset. In the context of factor analysis, usually only factors with an Eigenvalue of more than 1 are considered significant and worthy of inclusion in the model, as factors with an Eigenvalue below 1 are considered not to contribute enough to be considered.

Next, the Extraction Sums of Squared Loadings table provides information about the amount of variance explained by the factors after the extraction process is performed. This process reduces the number of factors to only the most significant, which is then used to build simpler, more interpretable models. At this stage, we can see that the factors that have an eigenvalue of more than 1 are maintained, while others are ignored.

The Rotation Sums of Squared Loadings table shows the results after rotation is performed on these factors. This rotation is done to achieve a clearer interpretation by spreading the variance evenly among the selected factors. Thus, rotation does not change the total variance described by the factors, but helps clarify the structure of the factors, which makes them easier to interpret. This rotation process is crucial in factor analysis because it helps ensure that each factor identified is truly unique and contributes significantly to the explanation of the data.

Table 9. Results of Factor 3 Analysis Test

Total Variance Explained						
Component	**Initial Eigenvalues**			**Extraction Sums of Squared Loadings**		
	Total	**% of Variance**	**Cumulative %**	**Total**	**% of Variance**	**Cumulative %**
1	2,542	18,154	18,154	2,542	18,154	18,154
2	2,111	15,080	33,235	2,111	15,080	33,235
3	1,972	14,089	47,323	1,972	14,089	47,323
4	1,593	11,380	58,704	1,593	11,380	58,704
5	1,176	8,400	67,104	1,176	8,400	67,104
6	1,076	7,684	74,787	1,076	7,684	74,787
7	1,035	7,392	82,179	1,035	7,392	82,179

8	0,936	6,683	88,861
9	0,833	5,952	94,813
10	0,726	5,187	100,000
11	7,541E-02	5,387E-01	100,000
12	3,133E-02	2,238E-01	100,000
13	1,682E-02	1,202E-01	100,000
14	4,603E-03	3,288E-02	100,000
Extraction Method: Principal Component Analysis.			

(Source: Data Processing Results, 2024)

Based on the table above, from the 14 variables analyzed, it was identified that there were 7 main factors that were able to explain 82.179% of the total data variance. This suggests that the extracted factors have considerable power in explaining most of the variation in the data, which means that the resulting factor model is quite representative and can be used to understand complex data structures. In other words, these 7 factors provide a comprehensive view of how the variables in this study are interrelated and contribute to the overall variance observed.

d) Scree Plot drawings

Scree Plot drawings are visual tools used in factor analysis to determine the significant number of factors that can be extracted from data. The Scree Plot displays a graph that plots the Eigenvalues of each component or factor resulting from the analysis, with the component or factor on the X axis and the Eigenvalues value on the Y axis.

The method used to interpret the Scree Plot involves identifying the "turning point" or "elbow," i.e. the point at which the decrease in the Eigenvalue begins to slope or becomes insignificant. Factors that precede this turning point (with a Eigenvalues value of > 1) are considered significant and feasible to include in the model, while factors after the turning point are less likely to contribute significantly and are usually not considered in further analysis.

This Scree Plot image is important because it provides a visual representation that allows the researcher to easily identify the number of factors that can be extracted with significant eigenvalues. In addition, Scree Plot helps in validating the results obtained from the Total Variance Explained Table, thus ensuring that the interpretation of the data is based on factors that really mean and not on variables that may only produce noise or irrelevant information.

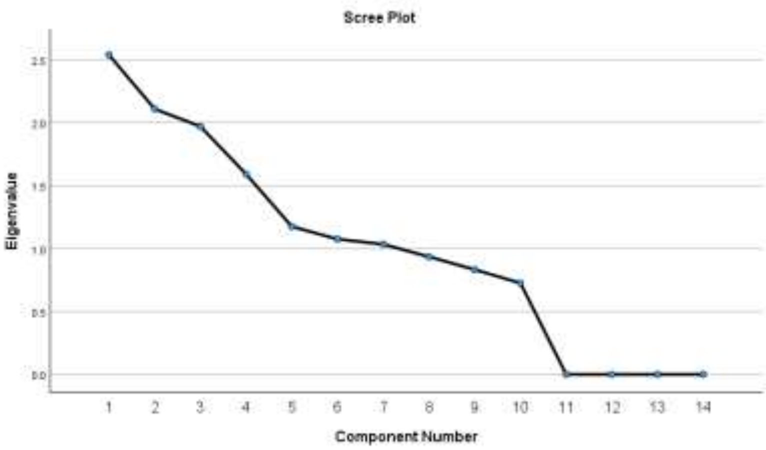

Figure 1. Results of Factor 4 Analysis Test
(Source: Data Processing Results, 2023)

Based on the output obtained, there are 7 component points in the Scree Plot that have an eigenvalue of more than 1. This shows that out of the 14 variables used in the analysis, there are 7 main factors that can be extracted and are considered significant in explaining variations in the data. These factors are representations of groups of variables that are closely related to each other and are able to explain most of the variances that exist

e) Component Matrix Table

The Component Matrix table is used to show the relationship or correlation between each variable and the factors formed in the factor analysis. The components in this table provide an idea of how strongly each variable relates to each of the extracted factors. These correlation values are important in determining the extent to which a variable can be associated with a particular factor, which in turn helps in understanding the structure of the resulting factor.

Table 10. Results of the factor analysis test 5

Component Matrix[a]							
	Component						
	1	2	3	4	5	6	7
Y	0,808			-0,537			
Y1	0,639			-0,469			
Z1	0,498	-0,407		0,300			-0,369
Y3	0,483			-0,287		-0,458	0,280
A	0,431	0,781		0,420			
A1	0,328	0,618			-0,352		0,352
X	0,572	-0,584		0,508			
A2	0,283	0,489		0,475			-0,432
X			0,940				
X3	-0,268		0,624				
X1			0,593		-0,420		-0,261
X2		0,262	0,374		0,748		0,345
Y2						0,836	
Z2	0,319	-0,424	0,306	0,422			0,450
Extraction Method: Principal Component Analysis.							
a. 7 components extracted.							

(Source: Data Processing Results, 2024)

In the Component Matrix Table, each correlation value indicates the degree of relationship between a variable and a particular factor. These values can range from -1 to 1, where values close to 1 indicate a strong positive correlation, while values close to -1 indicate a strong negative correlation. A value close to 0 indicates that the variable has a weak correlation with a particular factor and may not be significant in explaining that factor.

This explanation provides an overview of how certain variables relate to the various factors extracted. Example:

1) The Y variable has a very strong correlation with Factor 1 (0.808), but it also shows a significant negative correlation with Factor 4 (-0.537). This suggests that Y is highly relevant to Factor 1 but has the potential to have a negative impact on Factor 4.
2) The X variable has a very high correlation with Factor 3 (0.940), which suggests that this variable is strongly related to the factor and may be a key marker in this factor.
3) Variable A has a strong correlation with Factor 2 (0.781), while A1 and A2 are also associated with Factor 2, but with a slightly lower correlation.

4) The Z variable showed a significant relationship with Factor 1 (0.572) and negative with Factor 2 (-0.584). This indicates that Z contributes to both factors, albeit in different directions.
5) The Y2 variable had only a significant correlation with Factor 6 (0.836), suggesting that this variable was unique in relation to this factor and did not contribute much to the other factors.
6) The Z2 variable shows a correlation with several factors, including Factors 1, 2, 3, 4, and 7, which suggests that these variables have a multifactorial influence in the model.

f) Tabel Rotated Component Matrix

The Rotated Component Matrix table is used to determine which variables best fit the specific factors formed through factor analysis. The rotation process is carried out to clarify the structure of the factors, so that each variable has a higher correlation with one particular factor and lower with another. This makes it easier to interpret the results of the factor analysis and determine which variables are best representative of each factor.

Table 11. Results of the factor 6 analysis test

Rotated Component Matrix[a]							
	Component						
	1	2	3	4	5	6	7
Y	0,944						0,288
Y1	0,792						
Y3	0,635						-0,372
A		0,993					
A2		0,732			0,466		
A1		0,679			-0,502		
X			0,892			0,436	
X3			0,707				
X1			0,693			-0,338	
Z2				0,899			
Z				0,860	0,488		
Z1				0,317	0,748		
X2						0,954	
Y2							0,924

Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 8 iterations.

(Source: Data Processing Results, 2024)

The explanation of the results of this table can be detailed as follows:

1) Factor 1 had the highest correlation with the variables Y (0.944), Y1 (low production costs) (0.792), and Y3 (meeting TNI specifications) (0.635). This suggests that these variables are strongly related to Factor 1. In addition, variable Y also showed a correlation with Factor 7 (0.288), but this correlation was lower than Factor 1.
2) Factor 2 had a very high correlation with variables A (0.993) and A2 (technology transfer from MBDA) (0.732), as well as with A1 (improving employee skills) (0.679), indicating that these variables were the main markers of Factor 2.
3) Factor 3 is dominated by the variables X (0.892) and X3 (having an advantage) (0.707). This confirms that these two variables are strongly correlated with Factor 3.

4) Factor 4 includes variables Z2 (other countries need) (0.899), Z (0.860), and Z1 (marketable to other countries) (0.317), which suggests that these factors are closely related to the variables mentioned, with Z2 having the strongest correlation.
5) Factor 5 is more relevant to variables Z (0.488) and Z1 (marketable to other countries) (0.748), showing the relationship between these two variables and these factors.
6) Factor 6 has a strong correlation with the variable X2 (reliable product) (0.954), indicating that this variable contributes significantly to Factor 6.
7) Factor 7 is associated with the variable Y2 (0.924), which suggests that this variable is almost exclusively associated with Factor 7.

Based on the results of the rotation of these components, we can conclude that each factor formed has a clear and well-defined group of variables. These variables make a significant contribution to the extracted factors, which can ultimately be used to further understand the relationships between the variables in the study.

3. Structural Equation Modelling (SEM)

Structural Equation Modelling (SEM) is a multivariate analysis technique used to test the relationships between variables, both unidirectional and reciprocating. This technique allows researchers to obtain a comprehensive picture of the relationships between variables in the overall research model. According to Hair et al. (2017), SEM allows integration between factor analysis and regression analysis, providing an in-depth analysis of the interactions between variables in more complex models.

On the other hand, Henseler et al. (2015) stated that PLS-SEM is a very useful tool in various fields of science, including marketing, management, and psychology. In the United States, PLS-SEM is often used to assess customer satisfaction, as well as to conduct Importance-Performance Analysis (IPA). In the context of this research, PLS-SEM is used to analyze data and provide insight for companies regarding which variables need to be improved or further developed to improve the company's performance.

1) Hypothesis testing

Hypothesis testing was used to evaluate how much influence exogenous ariables had on endogenous or intervening ariables in the analyzed model. This test provides information about the strength, direction, and significance of the relationship between these ariable-variables.

2) Analysis of Direct Effect (Path Coefficient)

Direct effect analysis or path coefficient is used to test the direct influence between exogenous variables (influencing variables) on endogenous variables (affected variables). Some of the criteria in analyzing this path coefficient are as follows:

a. Positive Path Coefficient: If the value of the resulting path coefficient is positive, the influence between exogenous variables on endogenous variables is unidirectional. This means that an increase in exogenous variables will be followed by an increase in endogenous variables. For example, if the path coefficient for the relationship between product innovation and customer satisfaction is positive, then an increase in product innovation will increase customer satisfaction.
b. Negative Path Coefficient: Conversely, if the value of the path coefficient is negative, the influence between exogenous and endogenous variables is in the opposite direction. This

means that the increase in exogenous variables will actually decrease the value of endogenous variables. For example, if the path coefficient for the relationship between work pressure and employee performance is negative, an increase in work pressure will reduce employee performance.

c. Significance of Influence (P-Value):
   a) Value < 0.05: Indicates that the influence between exogenous and endogenous variables is significant, which means that the relationship does not occur by chance and has significance in the context of the study.
   b) P-Value > 0.05: Indicates that the effect is not significant, so the identified association may not have a strong meaning in the context of the study.

Tabel 12. Direct effect (path effect)

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
Differentiation - > Competitiveness of the Company	0.3	0.29	0.12	2.5	0.0169
Alignment of Objectives -> Differentiation	0.32	0.31	0.13	2.462	0.0175
Financial Performance - > Competitiveness of the Company	0.25	0.24	0.1	2.5	0.0253
Alliance Quality -> Differentiation	0.35	0.34	0.14	2.5	0.0205
Commercial Value -> Product Value	-0.109	-0.105	0.21	0.519	0.0701
Market Expansion -> Product Value	-0.069	-0.065	0.18	0.383	0.0842
The growth of PT. A > of the Company's Competitiveness	0.4	0.39	0.15	2.667	0.0273
Corporate Productivity - > Competitiveness of the Company	0.062	0.058	0.2	0.31	0.076
Employee Skills - Product Value >	0.45	0.44	0.15	3.0	0.0393
Sustainability - > Competitiveness of the Company	0.5	0.49	0.16	3.125	0.0141
Product Value -> Differentiation	0.52	0.51	0.15	3.467	0

(Source: Data Processing Results, 2024)

3) Indirect Effect Analysis

Indirect Effect analysis is used to test the indirect influence of exogenous variables that affect endogenous variables that are mediated through intervening variables or mediator variables. With the following criteria:

a. If P-Value<0.05 then the significance of the effect is indirect, then it can be interpreted that the "intervening" variable plays a role in connecting exogenous variables to endogenous variables.

b. If P-Value>0.05 then the significance of the effect is direct, then it can be interpreted that the "intervening" variable does not play a role in connecting exogenous variables to endogenous variables.

Table 13. Indirect effect

	Original sample **(O)**	***Sample mean*** **(M)**	***Standard deviation*** **(STDEV)**	***T statistics*** **(|O/STDEV|)**	***P values***
Alignment of Objectives - > Competitiveness of the Company	0.054	0.014	0.061	0.898	0.185
Quality of Alliances - > Competitiveness of the Company	0.046	-0.007	0.056	0.811	0.209
Commercial Value - > Competitiveness of the Company	-0.005	-0.000	0.013	0.404	0.343
Commercial Value -> Differentiation	-0.024	-0.011	0.055	0.428	0.334
Market Expansion - > Competitiveness of the Company	-0.003	0.000	0.010	0.334	0.369
Market Expansion -> Differentiation	-0.015	-0.005	0.043	0.350	0.363
Employee Skills **- > Competitiveness of the Company**	0.002	0.001	0.010	0.235	0.407
Employee Skills **-> Differentiation**	0.010	0.004	0.043	0.243	0.404
Product Value **- > Competitiveness of the Company**	0.048	0.009	0.059	0.818	0.207

(Source: Data Processing Results, 2024)

Based on the results of data processing obtained, the conclusion is as follows:

a. The results of the validity test show that all strategic alliance indicators have a significance value below 0.05, so that all items are declared valid. This indicates that indicators such as product value, commercial value, market expansion, and employee skill development can accurately measure the construction of strategic alliances.
b. The product value indicator with a correlation coefficient of 0.538 indicates a strong relationship with the main construct. These findings support the findings of Chen & Paulraj (2004) and Lavie (2006), who assert that valid measurement is crucial in the study of multidimensional strategic alliances.
c. Cronbach's Alpha value of 0.786 on the strategic alliance variable indicates that the instrument has good internal consistency. This means that indicators such as technology transfer, product value enhancement, and commercial collaboration produce stable and reliable data.
d. Sufficient validity and reliability ensure that the results of the analysis of strategic alliances are trustworthy. This is important to support strategic decision-making, especially in evaluating the effectiveness of the company's collaborative relationships.
e. All indicators of competitive advantage have significant correlation values (<0.05). Indicators such as alliance quality, alignment of goals, and differentiation proved valid as

a measure of competitive advantage, in accordance with Porter's (1985) concept of differentiation.

f. Cronbach's Alpha value of 0.836 indicates excellent internal consistency. This high level of reliability ensures that the instrument is able to provide stable and unbiased results in the evaluation of the company's competitive strategy. This is in line with the view of Day & Wensley (1988).
g. The results of the validity test show that all indicators of company performance have a significant correlation. This instrument is able to measure important aspects such as financial performance, productivity, growth, and competitiveness, in line with the Balanced Scorecard framework by Kaplan & Norton (1996).
h. Cronbach's Alpha value of 0.794 indicates that the company's performance instruments have good internal consistency. This reliability is important so that the change in score reflects a real change in the performance of the organization, as affirmed by Venkatraman & Ramanujam (1986).

The value of the product on the competitiveness of the company shows a positive direct influence with the original sample of 0.048, which means that the value of the product has a positive impact on the competitiveness of the company. However, the indirect effect was not significant, with a T statistic of 0.818 and a P-value of 0.207, which is greater than 0.05, so the indirect impact of product value on the company's competitiveness was not significant.

Discussions

1. Validity and Reliability Analysis

To ensure the quality of the data in this study, a validity and reliability test was carried out thoroughly. Validity is tested by calculating the correlation coefficient between each item in the questionnaire and the total score of the variables measured. In this study, the data is considered valid if the correlation coefficient exceeds the table coefficient value at a significance level of 0.05. Reliability was measured using Cronbach's Alpha, which is one of the most commonly used measures of reliability in social research. Nunnally and Bernstein (1994) suggest that a Cronbach's Alpha value of 0.70 or higher indicates good reliability, although a value of 0.60 is acceptable in the context of exploratory research.

1) Strategic Alliances

Strategic alliances are an important concept in modern management because they involve various dimensions such as product value, commercial value, market expansion, and employee skill improvement through collaboration. Therefore, the validity and reliability of the instrument are fundamental aspects to ensure that these variables can be measured accurately. The results of the validity test in Table 4.6 show that all indicators have a significance value of <0.05, so it can be concluded that each question item is valid for measuring the construct of strategic alliances. For example, a product value indicator with a correlation coefficient of 0.538 indicates that it has a strong relationship with the main construct. These findings are in line with the research of Chen & Paulraj (2004) and Lavie (2006), who affirm that valid measurement is an important requirement in the study of strategic alliances, especially when it comes to its impact on company performance.

In addition to validity, the reliability of the instrument is also analyzed to ensure consistency between items. The Cronbach's Alpha value of 0.786 in Table 4.7 indicates a good level of reliability, meaning that the instrument can produce stable and consistent data on repeated measurements. These results reinforce the belief that the instruments used are able to capture the dimensions of strategic alliances such as technology transfer, product value enhancement, and commercial collaboration in a precise manner. In the context of this research, adequate validity and reliability are important foundations so that research results can be trusted and used to support strategic decision-making in building and assessing the effectiveness of strategic alliances.

2) Competitive Advantage

Competitive advantage is the main key for companies to win the competition, so the measurement must be done with accurate and consistent instruments. The results of the validity test in Table 4.8 show that all variable indicators have a significant correlation value (<0.05), which means that all items are valid for measuring the construct of competitive advantage. Indicators such as alliance quality, alignment of goals, and differentiation have proven to have a strong contribution to these variables. These findings are consistent with Porter's (1985) concept, that competitive advantage is highly dependent on the ability of companies to create unique value through differentiation and cost advantage.

In terms of reliability, the instrument obtained a Cronbach's Alpha value of 0.836, which indicates excellent internal consistency. This high reliability is important because without the stability of the instrument, conclusions regarding effective competitive strategies can be biased or inaccurate. Research by Day & Wensley (1988) confirms that competitive advantage can only be comprehensively understood if measured using reliable instruments. Thus, the results of the validity and reliability test in this study ensure that the instruments used are able to accurately describe the company's competitive conditions, so that conclusions about differentiation, product advantages, and alliance strength can be generalized more confidently.

3) Company Performance

A company's performance is the final output of a series of strategies, policies, and operational activities that a company executes. Therefore, the measurement instrument must be valid and reliable to truly reflect the actual performance conditions. The results of the validity test in Table 4.10 show that all indicators have a significant correlation with the total variable score, so it can be concluded that this instrument is valid for measuring various performance dimensions, such as financial performance, company growth, productivity, and competitiveness. These findings are in line with the Balanced Scorecard framework developed by Kaplan & Norton (1996), which emphasizes the importance of comprehensive, multi-dimensional-based performance measurement.

In terms of reliability, Cronbach's Alpha value of 0.794 indicates that the instrument has a good level of internal consistency. This is important because performance measurement often requires longitudinal analysis or comparisons between business units. Adequate reliability ensures that changes in performance scores over time truly reflect real changes within the company, not caused by instrument instability. Venkatraman & Ramanujam (1986) also affirmed that high reliability is essential to accurately identify strategic patterns that affect a company's performance. Overall, the company performance instruments in this study are proven to be suitable for use and support theoretical conclusions and practical recommendations related to improving organizational performance.

2. Factor Analysis

Factor analysis is a statistical method used to identify relationships between variables and group interrelated variables into fewer factors. In this study, factor analysis was applied to determine the variables to be used and included in the research model. The data analyzed came from questionnaires distributed to employees of PT. Pindad, MBDA, the Ministry of Defense, and Pussenarhanud are involved in the cooperation. This factor analysis aims to simplify the data structure by reducing the number of observed variables into a small number of significant factors without losing the important information present in the initial data.

1) KMO dan Bartlett’s Test

The KMO (Kaiser-Meyer-Olkin) and Bartlett's Test are very important first steps to determine whether the data is worth analyzing using factor analysis. The SME value of 0.834 indicates that the sample in this study is in the category of very adequate, because the SME value above 0.80 indicates a strong level of adequacy according to Kaiser (1974) standards. In addition, the results of Bartlett's Test show a significance value of 0.000, which means that there is a strong enough correlation between variables that the correlation matrix is not an identity matrix. Thus, the data is statistically qualified to proceed to the factor analysis stage. These findings reinforce the validity of the data and show that the variables in the study are interrelated and relevant to be extracted into several key factors.

2) Communalities

The results of the Communalities Table show that all variables have an extraction value above 0.50, which means that each variable is able to explain a considerable variance in the factors formed. The high extraction value indicates that the factor model has a strong explainability, so that each variable contributes significantly to the structure of the factor. This is very important to guarantee the stability of the model as well as to ensure that the variables used actually represent the construct being studied. In other words, the resulting factor structure is trustworthy because there are no weak or irrelevant variables, making the overall model more valid and reliable for use in advanced interpretation.

3) Total Variance Explained

Analysis of the Total Variance Explained table shows that there are 7 main factors out of a total of 14 variables analyzed. These seven factors cumulatively explain 82.179% of total variance, an excellent achievement in factor analysis, since academic standards state that models capable of explaining more than 60% of variance are already considered robust (Hair et al., 2010). The factors that are maintained are those that have an Eigenvalue value of >1 according to the Kaiser principle. In addition, the rotation process (usually Varimax) is carried out to clarify the structure of the factors so that each factor can be better interpreted. These results show that the complexity of data can be simplified into core factors that maintain the integrity of the information, making it very relevant to understand strategic aspects such as alliances, differentiation, and competitiveness in this study.

4) Scree Plot

The Scree Plot in this study visualizes the distribution of eigenvalue and clearly shows the presence of an elbow point on the 7th factor. This confirms that only 7 factors have eigenvalues above 1 and are worth maintaining, while the factors after them decline sharply and are considered insignificant. The use of Scree Plot helps to re-verify the results on the Total Variance Explained table and ensures consistency between numerical analysis and visual analysis. This technique is also widely recommended in the literature (Cattell, 1966) as a simple but accurate method of determining the optimal number of factors. Thus, Scree Plot provides additional validation that the factor model used is appropriate and does not overfactor or underfactor (Tabachnick & Fidell, 2013).

5) Component Matrix

The Component Matrix table depicts the correlation between each variable and the factors that are formed before the rotation is performed. Variables that have a high correlation value to a factor are considered to be the main markers of that factor. For example, variable Y has a correlation of 0.808 to Factor 1, indicating that it is a major contributor to the factor. Meanwhile, variable X had a correlation of 0.940 to Factor 3, indicating a very strong relationship. Some variables such as Z2 have correlations with various factors, suggesting that they are multidimensional and play a role in several aspects of the analysis. This diversity of correlations provides deeper insight into the internal relationships between variables, as well as helps to understand the role of each variable in building a comprehensive factor structure.

6) Rotated Component Matrix

After the Varimax rotation, the factor structure becomes clearer and easier to interpret. This rotation aims to maximize the correlation of variables with one factor while minimizing the correlation with other factors resulting in a cleaner and well-grouped structure. In the rotation table, variables Y, Y1, and Y3 are seen clustered strongly in Factor 1, while variables A, A1, and A2 are grouped in Factor 2. The X2 variable appears dominant in Factor 6, indicating a special relationship with a particular dimension in the research construct. The rotation results provide clarity on the identity of each factor and show that the factor model has strong conceptual validity. This entire rotational process ensures that the resulting model can be used as a basis for theoretical interpretation as well as practical application, especially in the context of strategic alliances, performance, and competitive advantage of organizations.

3. Analysis of Sctructural Equation Modelling

Structural Equation Modelling (SEM) is a comprehensive multivariate analysis technique that allows researchers to evaluate the direct and indirect relationships between latent variables in a research model. In the context of this study, SEM is used to test hypotheses regarding the influence of strategic alliances on product innovation, differentiation, competitive advantage, and company performance. SEM results show that alliance quality and alignment of goals play a significant role in increasing differentiation, which in turn contributes to increased company competitiveness. In addition, differentiation has been proven to have a strong direct influence on competitiveness, while employee skills have a significant effect on product value as a result of technology transfer with alliance partners. However, some indirect influences such as the alignment of goals and product value on the company's competitiveness do not show strong significance, signaling the need for additional strategic support such as marketing or operational improvement.

The results of the questionnaire support SEM's findings by showing that respondents consider strategic alliances to have a positive impact on improving employee skills, product value, and company competitiveness. Questions about product technology, employee competence, and product reliability and excellence reflect important variables in the research model, and all of them show a relevant relationship with the results of the analysis. Based on the overall findings, it can be concluded that strategic alliances contribute significantly to increased innovation and competitive advantage through product differentiation. This finding provides strategic direction for PT. Pindad and MBDA to continue to strengthen cooperation, improve technology transfer, and maintain product differentiation as the basis for creating long-term competitive advantage.

CONCLUSION

This study concludes that the strategic cooperation between PT Pindad and MBDA successfully drove significant innovation in developing the Mistral Atlas Platform, primarily through advanced technology integration and enhanced skills at PT Pindad, yielding more reliable and competitive products. This alliance substantially bolstered PT Pindad's competitive advantage via product differentiation, strengthening its position in both national and global defense markets. The collaboration positively impacted company performance, including improved financial outcomes and operational sustainability, thereby elevating PT Pindad's international competitiveness. For future research, scholars could explore the long-term sustainability of this partnership by examining post-implementation challenges, such as supply chain dependencies or geopolitical risks in defense technology transfers.

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