THE EFFECT OF DRONE USE AND DIGITALISATION TRAINING ON WORK PERFORMANCE MEDIATED BY WORK MOTIVATION AT PTPN IV REGIONAL I

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ABSTRACT

PT Perkebunan Nusantara (PTPN) is currently undergoing a significant digital transformation phase by integrating drone technology into its plantation operations. PTPN already has Unmanned Aerial Vehicles (UAVs)/drones, which are mainly used for mapping areas and counting oil palm trees. The total plantation area of 101,733.53 hectares is supported by 36 drone units, with technology acceptance influenced by perceived usefulness and perceived ease of use. At PTPN IV, the proportional distribution of drones supports the perception that this technology is useful (speeding up monitoring) and easy to use (through training), thereby encouraging widespread adoption and increased productivity. The researchers aimed to analyse the effect of drone use and digitalisation training on work performance through work motivation. This study used a quantitative approach combined with descriptive qualitative data to reinforce the findings through interviews with structural equation modelling data analysis with a sample size of 83 employees. The results of the study indicate that digital transformation through the use of drones and digitalisation training plays an important role in increasing employee motivation and work performance at PTPN IV, although the effect is not entirely direct. The use of drones has been shown to be more dominant in driving work motivation than directly improving work performance, indicating that new technology tends to increase enthusiasm, interest, and perceptions of work progress before actually impacting performance output. Conversely, digitalisation training provides a more consistent and stronger contribution to work performance, both directly and through increased work motivation. Work motivation itself acts as an intervening variable that strengthens the relationship between technology and performance, although its direct influence on work performance is not yet fully optimal.

Keywords: Drone Utilization; Digitalization Training; Work Motivation; Job Performance; Digital Transformation

INTRODUCTION

The agricultural sector plays a crucial role in supporting human survival because it is greatly influenced by technical and environmental factors (Kusumaningrum, 2019). In addition to functioning as a provider of food, this sector is also one of the main contributors to the Indonesian economy (Saragih, 2010). In the third quarter of 2024, the contribution of the agricultural sector's Gross Domestic Product (GDP) reached 13.71 per cent of the total national GDP. Of this contribution, the plantation sub-sector remained the main driver of growth in the agricultural sector, contributing 4.96 per cent in the same period (Wahyudi et al., 2024).

Indonesian palm oil plantations, particularly in North Sumatra as one of the palm oil production centres, are transitioning towards precision agriculture through the implementation of digital transformation. This change is in line with global demands for high productivity that is sustainable and meets international standards such as the Roundtable on Sustainable Palm Oil (RSPO) and Indonesian Sustainable Palm Oil (ISPO). This transformation aims not only to increase crop yields, but also to streamline resource use, reduce operational costs, and minimise environmental impact (Akhtar et al., 2023).

Explain that the use of drones for mapping and inventorying equipped with multispectral sensors and artificial intelligence (AI) algorithms such as You Only Look

Once (YOLO) and Convolutional Neural Network (CNN) is capable of mapping vegetation and inventorying oil palm trees with an accuracy of more than 95% (Akhtar et al., 2023). The integration of drones with other digital technologies such as the Internet of Things (IoT) and artificial intelligence (AI) further strengthens their role in the concept of smart plantations. Image data collected by drones can be processed using AI algorithms to generate production forecasts, detect anomalies, and provide real-time data-based plantation management recommendations. This innovation supports plantations in achieving greater efficiency, adapting to climate change, and aligning with global sustainability standards, while also strengthening Indonesia's position as the world's largest palm oil producer.

The direct impact of implementing this technology is an increase in productivity and consistency of crop yields. Plantations that have adopted Internet of Things-based systems and data analysis have seen a 10–15% increase in fresh fruit bunch (FFB) yields per hectare per year, as well as a reduction in operational costs due to a 40% reduction in manual labour for field monitoring. Furthermore, digitally recorded data also facilitates the sustainability audit process for ISPO and RSPO certification, as each stage of production is recorded and verifiable (Iqbal, 2024). PT Perkebunan Nusantara (PTPN) is currently undergoing a significant digital transformation phase by integrating drone technology into its plantation operations. This modernisation does not stand alone, but is a continuation of previous digitalisation initiatives such as the implementation of Enterprise Resource Planning (ERP), the use of satellites for precision fertilisation, the e Panen application for monitoring crop yields, and digital block score cards for real-time evaluation of plantation performance. Currently, PTPN IV Regional I manages a total plantation area of 101,733.53 hectares in its operational area. PTPN IV's palm oil production has fluctuated, although the ups and downs have not been significant. This has encouraged PTPN IV to continue to increase palm oil production and utilise drones, mainly for mapping areas and counting palm trees.

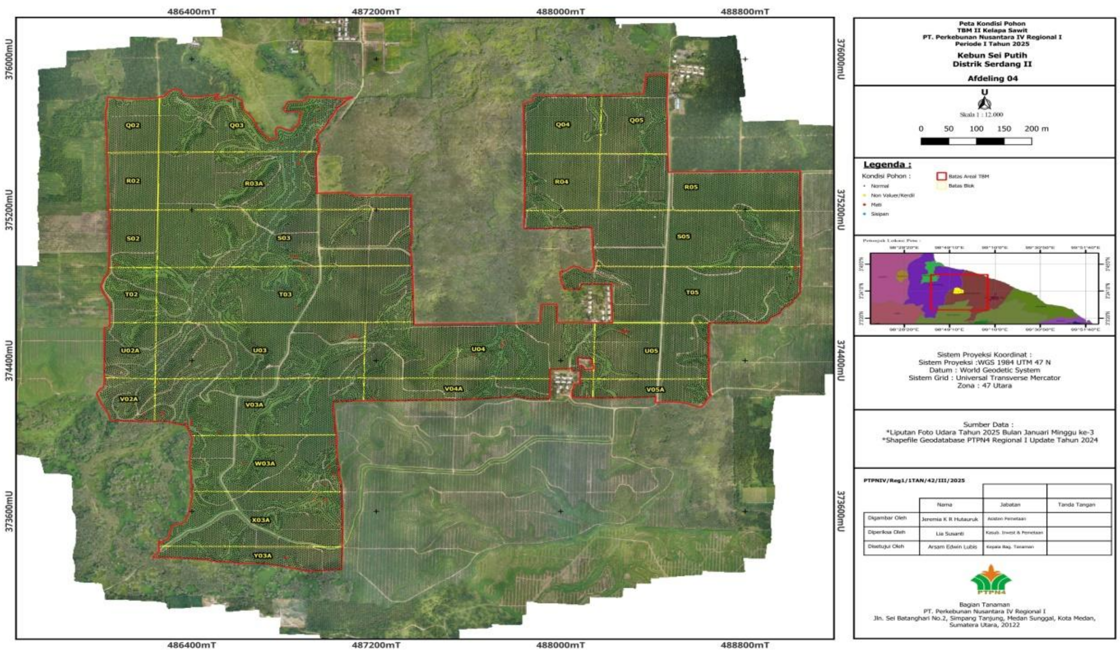

Figure 1. Land Mapping with Drones PT. Perkebunan Nusantara IV Regional I

The results of drone mapping at the Sei Putih Afdeling 04 plantation, PT Perkebunan Nusantara IV, show a detailed spatial overview of the management of oil palm plantation land. These high-resolution images display the concession boundaries marked by clear red lines, enabling accurate identification of productive and non-productive areas.

Rahim et al., (2023) found that when employees were introduced to drone technology, they experienced an increase in self-efficacy, which is an individual's belief in their ability to complete tasks. In the context of plantations, workers who previously performed manual tasks such as tree counting or pest spraying are now equipped with the skills to operate drones, which requires new technical knowledge such as UAV navigation, aerial image interpretation, and spatial data analysis. This training process shapes new perceptions of competence, making workers feel more professional and adding value in the eyes of the plantation. This increased confidence has a direct impact on their readiness to take on more complex and innovative tasks.

The use of drones at PTPN IV shows a proportional distribution of the drone fleet in relation to the total area of plantations managed in various divisions. The total plantation area of 101,733.53 hectares is supported by 36 drone units, with technology acceptance influenced by perceived usefulness and perceived ease of use. At PTPN IV, the proportional distribution of drones supports the perception that this technology is useful (speeding up monitoring) and easy to use (through training), thereby encouraging widespread adoption and increased productivity. According to Nadzuar et al., (2024), the use of drones for land mapping and crop health monitoring reduces manual labour and speeds up the field data collection process, which previously took weeks, to just a few days. This is in line with the findings of Rahim et al., (2023), who stated that drone-based automation allows for the allocation of labour to high-value tasks, thereby increasing engagement and job satisfaction.

To accelerate the digitisation process in each plantation and unit, the company has provided one Phantom drone for each plantation and trained one assistant department head and one implementing employee. Additionally, to support digitalisation, operational staff are provided with training, as evidenced by SEVC Business Support Instruction No. BSDM/MO/7.5i-3/2023 regarding the implementation of GIS and drone training. Drone technology training in the palm oil plantation sector has proven to be a key factor in improving employee competence and performance. This is based on Arief et al.,(2024), which shows that structured training, ranging from theory to field practice, can improve workers' skills in land mapping, aerial image analysis, and spatial data management. According to Veritia et al., (2024), training in the use of digital technologies such as drones in plantations not only improves workers' technical competencies but also builds their confidence and pride in the company. This increase in motivation has a direct impact on the company's operational efficiency and productivity, making drone technology one of the main catalysts for human resource management transformation in the plantation sector.

However, in reality, many trained assistants and executive staff have encountered several obstacles. Among them is the fact that these employees are not specifically trained in drone piloting and digitisation, but are employees who already have other jobs, thus adding to their workload. Meanwhile, for department assistants, in addition to being an additional task outside their duties as department assistants, it also causes concern for them because some department assistants lack the necessary competencies, so they worry that their work will be captured by aerial photography. Based on this explanation, the researcher decided to conduct further research with the title ‘The Effect of Drone Use and

Digitalisation Training on Work Performance Mediated by Work Motivation at PTPN IV Regional I.

RESEARCH METHODS

This research was conducted at PT. Perkebunan Nusantara IV Regional I PalmCo. The research area was determined purposively, based on several issues or phenomena related to the use of drones and digitalisation training on work performance through employee motivation at PTPN IV Regional I. The research was conducted from July to August 2025.

Research Methods and Approaches

The research approach used in this study is quantitative, reinforced by descriptive qualitative data. The quantitative approach is used to analyse the use of drones and digitalisation on work motivation through work performance in order to determine the factors that influence this. The qualitative data will be used to comprehensively describe the factors studied in increasing work motivation through work performance. The two-method approach used can produce quantitative and qualitative data. The data collected based on the quantitative approach is primary data collected through a survey. The survey in this case is in the form of a questionnaire. Then, the results based on the primary survey are reinforced with qualitative methods, which interpret the results in depth for the study.

Sampling Method

The method used in sampling in this study is based on the census method or Non-Probability Sampling. This Non-Probability Sampling technique does not give all elements in the population an equal chance of being selected as samples. The approach in Non-Probability Sampling is a saturated sampling (census) approach.

Therefore, the saturated sampling technique was used, where the entire population was used as the sample. Sampling was carried out using the saturated sampling technique based on drone users and digitisation among assistants and employees who had been trained throughout the PTPN IV Regional 1 plantation during 2022-2023. In this case, there were 83 employees.

Data Analysis Method

In this study, hypothesis testing was conducted using a Partial Least Square (PLS)-based Structural Equation Model (SEM) approach, often abbreviated as SEM-PLS. Each hypothesis was analysed using Smart PLS version 3.0 software to evaluate the relationships between variables. SEM-PLS is an alternative to SEM analysis, especially when data does not follow a normal distribution. Therefore, this method is known as a soft modelling technique because it has more flexible requirements than conventional SEM, for example in terms of measurement scale, sample size, and residual distribution. The application of SEM-PLS follows specific procedures in defining the research model, which includes the inner model and outer model. After that, data collection and validation are carried out, followed by an evaluation of the model used and analysis of the research results. The stages in using SEM-PLS can be explained as follows:

Outer Model

In research using Structural Equation Modelling (SEM), the outer model is part of the measurement model that explains the relationship between latent variables and the indicators used to measure them. The main function of the outer model is to test the validity and reliability of the construct, so that it can be ensured that the indicators used truly reflect the latent variables being measured. In SEM, the outer model is divided into two main types, namely reflective and formative.

According to Hair et al., (2019), in a reflective model, indicators are manifestations of latent variables, so that any change in latent variables will be reflected in the indicators. Conversely, in a formative model, indicators collectively form latent variables, so that changes in one indicator do not always directly affect the latent variables as a whole.

Inner Model

In research using Structural Equation Modelling (SEM), the inner model is part of the structural model that describes the causal relationships between latent variables in a research system. The inner model serves to test the relationships between latent constructs, both directly and indirectly, in order to understand the patterns of interrelationships between variables in the developed model.

The inner model is used to test hypotheses and measure the extent to which latent variables influence each other. This evaluation is carried out through several indicators, such as path coefficient, R^2 (coefficient of determination), f^2 (effect size), and t-statistic. This model plays a role in determining the extent to which independent variables can explain dependent variables in the research conducted.

SEM Model

The Structural Equation Modelling (SEM) model in this study was designed to analyse the causal relationship between the use of modern technology, such as drones and digitalisation, and employee work motivation and performance in the plantation sector. This model adopts the Partial Least Squares (PLS-SEM) approach, which is suitable for use in conditions where the data is not normally distributed and the sample size is relatively small. In this study, there are three main latent variables, namely Drone Use (X1), Digitalisation Training (X2), work motivation (Z), and work performance (Y).

The drone use variable (X1) reflects the level of drone utilisation in supporting operational work on plantations. The indicators used in this variable (X1.1 – X1.10) measure the extent to which drone technology helps with work efficiency, accuracy, and safety. Meanwhile, the digitalisation training variable (X2) represents the extent to which knowledge sharing related to digitalisation is applied in the work environment, which is reflected in ten indicators (X2.1 – X2.10). These two variables act as exogenous variables that are hypothesised to have a direct influence on Work Performance (Y).

The work motivation variable (Z) acts as a mediator linking the influence of technology on employee performance. With indicators Z1.1 – Z1.10, this variable evaluates how the application of drones and digitalisation affects employee morale, satisfaction, and engagement at work. Increased work motivation is expected to contribute to work performance (Y), which is an endogenous variable in this model. Work performance (Y) is measured through ten indicators (Y1.1 – Y1.10) that assess aspects of productivity, efficiency, work quality, and compliance with operational procedures.

Structurally, this model illustrates that the use of drones and digitalisation knowledge sharing has an influence on work motivation, which in turn has an impact on improving employee work performance. The PLS-SEM approach is used to test the strength of the relationship between variables with indicators such as path coefficient, R^2 (coefficient of determination), f^2 (effect size), and t-statistic values to measure the significance of causal relationships. Thus, this study aims to provide empirical insights into the effectiveness of technology implementation in improving workforce performance in the plantation sector through increased work motivation.

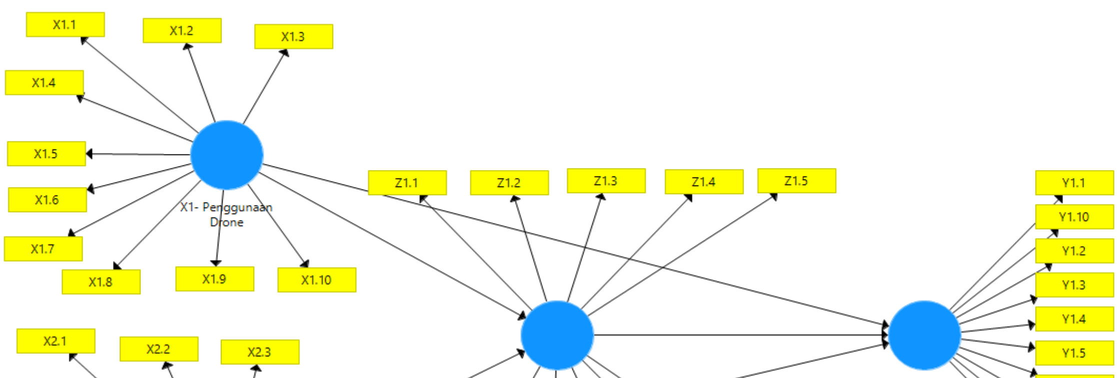

Figure 2. SEM Model

RESULT AND DISCUSSION

The Outer Model

The outer model test in this study was conducted to evaluate the quality of the measurement model, particularly in ensuring that each indicator is able to represent the latent construct that is measured validly and reliably. Outer model testing is an important stage in Partial Least Squares-based Structural Equation Modelling analysis Least Squares (SEM-PLS), because the results of structural analysis (inner model) can only be interpreted correctly if the measurement model has met the required feasibility criteria.

According to Hair et al., (2019), the outer model aims to assess the relationship between latent constructs and their indicators, so that it can be determined to what extent the indicators adequately contribute to explaining the constructs they represent. Hair et al., (2019) emphasise that good indicators must have high outer loading values, which indicate a strong correlation between the indicators and latent constructs. The higher the outer loading value, the greater the ability of the indicator to explain the variance of the measured construct.

In line with this opinion, Ghozali & Latan, (2015) states that the evaluation of the outer model in SEM-PLS aims to test convergent validity, discriminant validity, and construct reliability. Convergent validity is evaluated through outer loading values and Average Variance Extracted (AVE), while construct reliability is assessed through Composite Reliability and Cronbach's Alpha values. Indicators with outer loading values that meet the criteria indicate that the indicators consistently and accurately measure the intended construct.

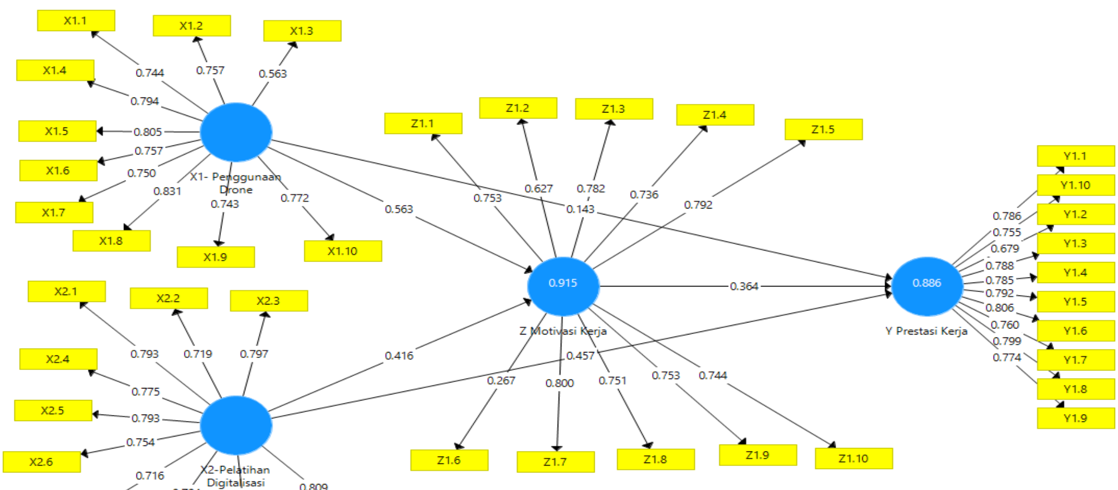

Figure 3. Outer Model

Based on the measurement model shown in the figure above, this study is constructed on the constructs of Drone Use (X1) and Digitalisation Training (X2) as independent variables, Work Motivation (Z) as an intervening variable, and Work Performance (Y) as a dependent variable. The direction of the arrows connecting the constructs indicates the causal relationships tested in the model, where the use of drones and digitalisation training not only have a direct effect on work performance but also have an indirect effect through work motivation as a mediating variable.

Outer Loadings Use of Drones

The indicator with the highest outer loading value is reducing work errors with a value of 0.831. This result shows that the ability to use drones to minimise work errors is the most dominant aspect and most strongly represents the construct of drone use. This high value indicates that respondents strongly feel that drones play a role in improving the accuracy and reliability of work performance, thereby reducing the potential for errors that can occur in conventional work processes. This is supported by (Zhang & Kovacs, 2012), who emphasise that Unmanned Aerial Vehicles (UAVs/drones) significantly reduce human error in data collection and land monitoring compared to manual methods. This is related to the ability of drones to produce accurate and consistent geospatial data, thereby reducing the risk of human error in the measurement and observation process.

Outer Loadings Digitalisation Training

The indicator with the highest outer loading value is improving performance with a value of 0.809. This shows that the impact of digitalisation training on improving employee performance is the most dominant and strongest aspect in representing the construct of digitalisation training. This high value indicates that respondents really feel the contribution of digitalisation training in improving their effectiveness, quality, and work results. Based on Salas et al., (2012), training designed based on work needs and technology has been proven to significantly improve individual and organisational performance. Digital training enables employees to work faster, more accurately, and adapt more quickly to changes in the work system. Boadu et al., (2018) state that technology-based training contributes directly to performance improvement through increased digital competence and work process efficiency.

Outer Loadings Work Motivation

The indicator with the highest outer loading value is job satisfaction with a value of 0.800. This finding shows that satisfaction with the work environment in terms of physical conditions, work relationships, and organisational atmosphere is the most dominant aspect in shaping employee work motivation. This high value indicates that a conducive work environment is a key factor that drives employees' enthusiasm and internal motivation to work optimally. Work engagement in the Job Demands Resources Model framework, where work motivation arises when employees have adequate job resources.

These resources include a supportive work environment, harmonious working relationships, support from superiors, clarity of roles, and opportunities for self-development. When these resources are available, employees tend to show a high level of work engagement, which is reflected in their internal drive to work optimally. A positive work environment then acts as the main trigger for work engagement. A safe, fair, and supportive environment not only reduces work fatigue but also increases psychological energy (vigor) and emotional commitment to work (dedication) (Bakker & Albrecht, 2018).

Outer Loadings Work Performance

The indicator with the highest outer loading value is cost efficiency, with a value of 0.806. This high value indicates that respondents view cost efficiency as the main measure of performance success, reflecting the ability to work optimally with more economical and controlled use of resources. Cost efficiency shows that employee performance is most strongly perceived through the ability to produce work output with optimal use of resources. In the context of modern organisations, especially in the operational and plantation sectors, performance is no longer measured solely by the volume or speed of work, but by the ability to reduce costs without compromising the quality of results. Theoretically, cost efficiency is a manifestation of effective performance because it reflects the ability of employees to utilise time, technology, and resources rationally. Employees who are able to work efficiently are considered to provide direct added value to the organisation, especially in the face of cost pressures and productivity demands (Neely et al., 2005). Overall, the results of this outer loading test show that some constructs in the study do not meet the convergent validity category, so indicators that do not meet the requirements will be removed. Thus, the outer loadings that can be used are as follows:

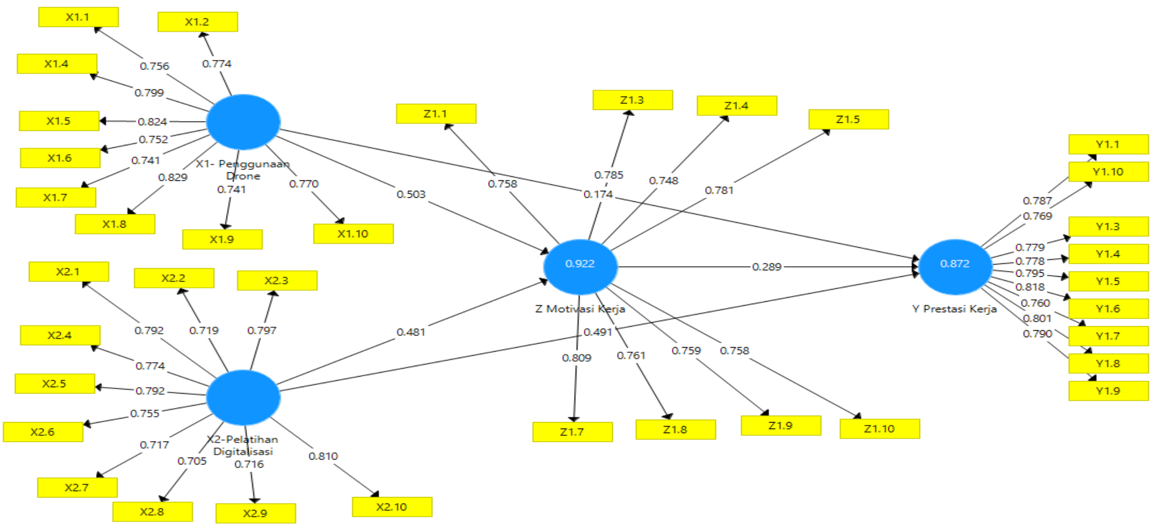

Figure 4. Outer Model II

After removing invalid indicators, the outer loading results in the table above show that all indicators used in each variable of Drone Use (X1), Digitalisation Training (X2), Work Performance (Y), and Work Motivation (Z) have outer loading values above the minimum required limit. This indicates that each indicator has made an adequate contribution in reflecting the latent construct it represents. Thus, the measurement model used at this stage has met the overall convergent validity criteria.

With the convergence validity criteria met for all constructs, the measurement model (outer model) is declared feasible to proceed to the next testing stage. Next, the analysis will focus on testing other outer models, namely construct reliability through Composite Reliability and Cronbach's Alpha values, as well as discriminant validity to ensure that each construct has a clear measurement uniqueness and does not overlap with other constructs.

Testing the Validity and Reliability of the Measurement Model

Construct reliability testing in SEM-PLS aims to assess the extent to which indicators within a construct consistently represent the same concept. Construct reliability is generally evaluated through Composite Reliability and Cronbach's Alpha, where high values indicate that the indicators have strong internal correlations (Hair et al., 2019).

Table 1. Testing the Validity and Reliability of the Measurement Mode

	Cronbach's Alpha	*Composite Reliability*	*Average Variance Extracted (*AVE*)*
X1- Use of Drones	0,918	0,932	0,603
X2- Digitalisation Training	0,918	0,931	0,575
Y Work Performance	0,923	0,936	0,619
Z Work Motivation	0,902	0,921	0,593

Source: Processed Primary Data (2026)

1. Drone Use (X1)

The Drone Use construct shows a very good level of reliability, reflected in a Cronbach's Alpha value of 0.918 and a Composite Reliability of 0.932, both of which far exceed the recommended minimum limit of 0.70. This indicates that all indicators in this construct have high internal consistency and stably represent the concept of drone use in the context of company operations. In addition, the AVE value of 0.603 has met the convergent validity criteria (>0.50), indicating that more than 60 per cent of the indicator variance can be explained by the Drone Use construct. Thus, this construct can be declared reliable and valid for use in further analysis.

2. Digitalisation Training (X2)

The Cronbach's Alpha value of 0.918 and Composite Reliability of 0.931 in the Digitalisation Training construct indicate a very strong level of reliability. The internal consistency of the digitalisation training indicators is in the very good category, which indicates that training programmes, digital competency improvement, and technology utilisation are measured consistently by the research instrument. The AVE value of 0.575 also exceeded the required threshold, so this construct was declared to have adequate convergent validity. This means that the digitalisation training indicators are able to explain the construct substantially and relevantly.

3. Work Performance (Y)

The Work Performance construct has a Cronbach's Alpha value of 0.923 and a Composite Reliability of 0.936, reflecting very high reliability. This indicates that indicators such as productivity, work quality, time and cost efficiency, and reporting accuracy are strongly correlated in measuring employee work performance. The AVE value of 0.619 indicates that most of the indicator variance can be explained by the work performance construct itself. Thus, this construct is not only reliable but also has excellent convergent validity.

4. Work Motivation (Z)

The Work Motivation construct shows a Cronbach's Alpha value of 0.902 and a Composite Reliability of 0.921, which indicates a high level of internal consistency of the indicators. Work motivation indicators, such as work targets, work goals, rewards, and career development, consistently reflect the work motivation construct. The AVE value of 0.593 meets the established criteria, so it can be concluded that this construct has adequate convergent validity. This indicates that work motivation as an intervening variable is measured accurately and is suitable for use in structural model testing.

R-Square coefficient

The coefficient of determination (R-Square) represents the proportion of variance in the endogenous (dependent) variable that is explained by the exogenous (independent) variables specified in the structural model. The remaining unexplained variance is attributable to factors not included in the model. Consequently, a higher R-Square value reflects a stronger explanatory capability of the model and indicates that the proposed model provides a better representation of the relationships among the research variables.

Table 2. R-Square Coefficient

	R Square	*R Square Adjusted*
Y Work Performance	0,872	0,867
Z Work Motivation	0,922	0,920

Source: Processed Primary Data (2026)

The analysis results show that the R-Square value for the Work Performance variable (Y) is 0.872, with an Adjusted R-Square value of 0.867. These findings indicate that 87.2% of the variation in employee Work Performance can be explained by the variables of Drone Use, Digitalisation Training, and Work Motivation contained in the research model. Meanwhile, the remaining 12.8% is influenced by other factors outside the model that were not examined in this study. This high R-Square value indicates that the model has a very strong explanatory power in explaining the determinants of employee work performance.

Furthermore, the R-Square value for the Work Motivation (Z) variable is 0.922, with an Adjusted R-Square of 0.920. This indicates that 92.2% of the variation in employee Work Motivation can be explained by the variables of Drone Use and Digitalisation Training. This value indicates that these two independent variables have a very dominant contribution in shaping employee work motivation. The high R-Square value in the Work Motivation construct reflects that the application of drone technology and digitalisation training are the main factors that influence the psychological condition and work attitude of employees.

Inner Model

Structural model testing (inner model). This stage focuses on testing the causal relationships between latent constructs that have been formulated in the conceptual framework of the study. According to Hair et al., (2019), the evaluation of the inner model aims to assess the strength and direction of the relationships between latent variables, while also testing the model's ability to explain dependent variables through path coefficients, coefficient of determination (R^2) values, and the significance of direct and indirect effects. In other words, the inner model is used to answer the main research question regarding whether and to what extent independent variables influence dependent variables, both directly and through mediating variables.

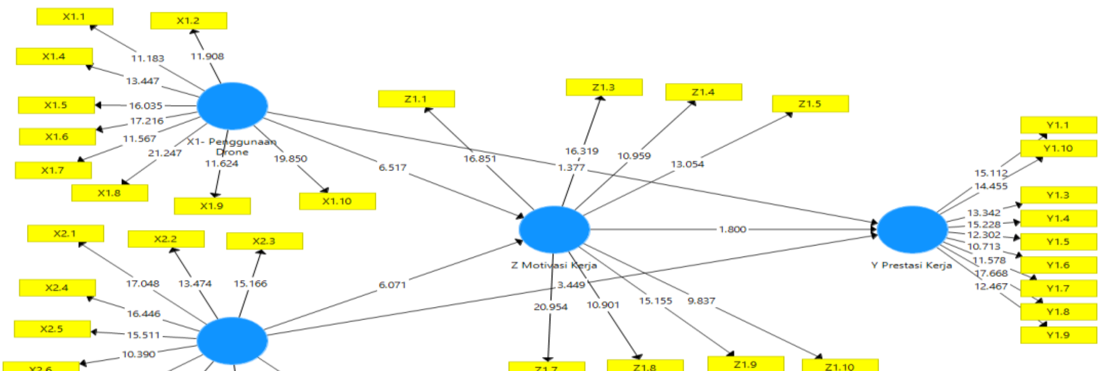

Figure 5 Boostraping
Source: Processed Primary Data (2026)

Uji t-Statistik

The results of the hypothesis testing using the bootstrapping procedure are presented in Table 3. The significance of each hypothesized relationship was evaluated based on the t-statistic and p-value.

Tabel 3 Uji t-Statistik

	Original Sample (O)	*Sample Mean (M)*	*Standard Deviation (STDEV)*	*T Statistics (|O/STDEV|)*	*P Values*
X1- Use of Drones -> Y Work Performance	0,174	0,212	0,127	1,377	0,169
X1- Use of Drones -> Z Work Motivation	0,503	0,519	0,077	6,517	0,000
X2-Digitalisation Training -> Y Work Performance	0,491	0,477	0,142	3,449	0,001
X2-Digitalisation Training -> Z Work Motivation	0,481	0,465	0,079	6,071	0,000
Z Work Motivation -> Y Work Performance	0,289	0,266	0,161	1,800	0,073

Source: Processed Primary Data (2026)

The Use of Drones Affects Work Performance

The test results show that the relationship between the use of drones (X1) and work performance (Y) has a path coefficient value of 0.174, with a t-statistic value of 1.377 and a p-value of 0.169. This value does not meet the criteria for statistical significance at a 95 per cent confidence level. Thus, H1 is rejected, meaning that the use of drones does not yet have a significant direct effect on employee work performance. Substantively, a coefficient value of 0.174 indicates that each one-unit increase in drone use can only increase work performance by 0.174 units, and this increase is not strong enough to be considered statistically significant.

The application of advanced technology does not always have a direct impact on performance improvement, especially when the technology adds to the complexity of the work, cognitive demands, and new responsibilities for employees. Tarafdar et al., (2019) explain that digital technology can trigger technostress creators, such as techno overload and techno complexity, which require employees to work faster, learn new systems, and allocate additional energy outside of their main tasks. This situation causes fatigue and reduces work focus, so that performance improvements are not immediately achieved even though the technology has been implemented.

Digitalisation Training Affects Work Performance

The test results show that Digitalisation Training (X2) has a positive and significant effect on Work Performance (Y) with a coefficient value of 0.491, a t-statistic value of 3.449, and a p-value of 0.001. Therefore, H3 is accepted. Interpretatively, this value indicates that every one-unit increase in digitalisation training will increase employee work performance by 0.491 units. This finding confirms that digitalisation training is a very important factor and plays a direct role in improving employee performance.

Based on the findings of Muhlis & Marayasa (2025), training has been proven to have a significant effect on work performance because it can directly improve employees' work abilities in terms of knowledge, skills, and accuracy in performing tasks. The study confirms that employees who participate in training have a better understanding of their work, are able to complete their work according to operational standards, and show an increase in productivity and quality of work.

The Use of Drones Affects Work Motivation

The test shows that the use of drones (X1) has a positive and significant effect on work motivation (Z) with a coefficient value of 0.503, a t-statistic value of 6.517, and a p-value of 0.000. Thus, H2 is accepted. This coefficient value indicates that every one-unit increase in drone use will increase employee work motivation by 0.503 units. This finding indicates that the use of drones provides a strong psychological boost, such as increased work enthusiasm, interest in technology, and the perception of ease in performing tasks.

The impact of digital technology affects employee work motivation through various integrated psychological and structural mechanisms. The application of digital technology, particularly through digital technology and technology-based work systems, can increase employees' sense of competence and confidence because they feel they have the skills relevant to the demands of the job. In addition, digital technology provides faster, more objective, and transparent performance feedback, so that employees have clarity regarding their roles, targets, and work achievements (Al-kharabsheh et al., 2023).

Digitalisation Training Affects Work Motivation

The relationship between Digitalisation Training (X2) and Work Motivation (Z) shows a coefficient value of 0.481, with a t-statistic of 6.071 and a p-value of 0.000. Thus, H4 is accepted. This coefficient value indicates that every one-unit increase in digitalisation training will increase employee work motivation by 0.481 units. This shows that digital training not only improves technical competence but also strengthens employee confidence and work engagement.

Based on the research by Iskandar et al., (2025) at the Head Office of PT Perkebunan Nusantara IV Medan, training has been proven to play an important role in increasing employee work motivation because training is positioned as a planned learning process that is directly related to job requirements, skill improvement, and clarity of employee roles in the organisation.

Work Motivation affects Work Performance

The test results show that Work Motivation (Z) has a positive effect on Work Performance (Y) with a coefficient value of 0.289, a t-statistic value of 1.800, and a p-value of 0.073. This value does not meet the significance criteria at the 5 per cent level, so H5 is rejected. However, in terms of the direction of the relationship, the coefficient value indicates that every one-unit increase in work motivation will increase work performance by 0.289 units, even though this increase is not statistically significant. This indicates that work motivation tends to act as a supporting factor that strengthens the influence of other variables, particularly the use of drones and digitalisation training.

The fact that work motivation does not have a significant effect on the work performance of employees at PT. Frisian Flag can be explained by the characteristics of the work and the work system in place at the company. A structured work environment, with strict standard operating procedures and clearly defined work targets, means that employee work performance is determined more by compliance with rules, technical skills, and work stress management than by internal motivation. In such conditions, even if employees have high work motivation, the space to express that motivation into improved work performance becomes limited (Aldi & Susanti, 2019).

Specific Indirect Effect Results

The results of the Specific Indirect Effects analysis obtained through the bootstrapping procedure are presented in Table 4. This analysis evaluates the significance of the indirect relationships among variables through the mediating construct based on the indirect path coefficient, t-statistic, and p-value.

Tabel 4. Spesific Indirect Effect

	Specific Indirect Effects
X1- Use Of Drone -> Z Work Motivation -> Y Work Perfomance	0,146
X2-Digitalisation Training -> Z Work Motivation -> Y Work Perfomance	0,139

Source: Processed Primary Data (2026)

The use of drones affects work performance through work motivation

The results of testing specific indirect effects show that the path from drone use (X1) → work motivation (Z) → work performance (Y) has an indirect coefficient value of 0.146. This value indicates a positive indirect effect, suggesting that the use of drones can improve employee work performance through increased work motivation. Substantively, this means that every one-unit increase in drone use will increase work performance by 0.146 units through work motivation.

In the study by Al-kharabsheh et al., (2023), it was found that digital-based performance technology systems, such as the use of real-time platforms, performance dashboards, or data-based feedback, not only function as measurement tools but, more importantly, serve as powerful motivators. When employees receive transparent, objective, and rapid assessments through digital channels, they feel recognised, understand expectations more clearly, and feel they are being treated more fairly.

Digitalisation Training Affects Work Performance through Work Motivation

The results of the specific indirect effects test on the Digitalisation Training (X2) → Work Motivation (Z) → Work Performance (Y) pathway show a coefficient value of 0.139. This value indicates that digitalisation training has a positive indirect effect on work performance through increased work motivation. This means that every one-unit increase in digital training will increase work performance by 0.139 units through work motivation. These findings indicate that work motivation is an important channel that strengthens the impact of digital training on employee performance, although its indirect contribution is relatively smaller than the direct effect of digital training on work performance.

The results of the study by Al-kharabsheh et al., (2023) show that digital training not only directly increases employee work motivation but also indirectly contributes to improving their performance through increased motivation. This indirect pathway is significant with a coefficient of β = 0.112 and p = 0.003, indicating that work motivation acts as an effective mediator.

The Effect of Drone Procurement and Digitalisation Training on Work Performance Through Work Motivation

The results of the F-Square (effect size) analysis are presented in Table X. This analysis evaluates the magnitude of the contribution of each exogenous construct to the endogenous construct in the structural model.

Tabel 5. Uji F-Square

	Y Work Perfomance	Z Work Motivation
X1- Use Of Drone	0,027	0,596
X2-Digitalisation Training	0,223	0,546
Y Work Perfomance		
Z Work Motivation	0,051	

Source: Processed Primary Data (2026)

In general, the F^2 values indicate effect size within the structural model. Use of Drone (X1) has a very small effect on Work Performance (Y) ($F^2 = 0.027$) but a moderate effect on Work Motivation (Z) ($F^2 = 0.596$), suggesting that drone utilization primarily enhances employees' motivation rather than directly improving performance. Similarly, Digitalisation Training (X2) shows a small effect on Work Performance (Y) ($F^2 = 0.223$) and a moderate effect on Work Motivation (Z) ($F^2 = 0.546$), indicating that digital training initiatives are more influential in strengthening motivation than in generating immediate performance outcomes. Furthermore, the effect of Work Motivation (Z) on Work Performance (Y) is very small ($F^2 = 0.051$), implying that motivation alone may not be sufficient to substantially improve performance and that other organizational or contextual factors may play a significant role.

CONCLUSION AND SUGGESTION

Overall, the findings of this study indicate that digital transformation through drone utilization and digitalization training plays a significant role in enhancing employee motivation and job performance at PTPN IV, although the effects are not entirely direct. Drone utilization is found to have a stronger influence on work motivation than on job performance, suggesting that new technologies tend to first improve employees' enthusiasm, engagement, and perceptions of work advancement before translating into tangible performance outcomes. In contrast, digitalization training demonstrates a more consistent and substantial contribution to job performance, both directly and indirectly through increased work motivation. Work motivation functions as an intervening variable that strengthens the relationship between digital initiatives and performance, even though its direct effect on job performance is not yet fully optimal.

The recommendation in this research wa digitalization training shows a more consistent and substantial contribution to work performance, both directly and indirectly thru increased work motivation

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