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The Effect of Condition-Based Maintenance (CBM), Operational Environment Conditions (OEC) and Human Resource Competency (HRC) on Forklift Engine Performance

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ABSTRACT: Forklifts are the main equipment in the goods management system in warehouses that have an important role in increasing productivity, operational efficiency, and smooth logistics flows. If the performance of the forklift decreases, there will be an increase in downtime, more expensive maintenance costs, and the risk of disruption in operations. This study aims to analyze the influence of Condition-Based Maintenance (CBM), Operational Environment Conditions (OEC), and Human Resource Competency (HRC) on heavy equipment performance, namely Heavy Equipment Performance (HEP), in forklift operations in warehouses. Forklift performance is measured through indicators such as transportation productivity, downtime frequency, and maintenance cost efficiency. Meanwhile, CBM, OEC, and HRC are represented by various technical, environmental, and workforce competency indicators. This study uses a quantitative approach with a causal-explanatory design. Data were collected through a Likert Scale-based questionnaire survey of 49 respondents, consisting of operators, technicians, and supervisors, using purposive sampling methods. Data analysis was carried out using the Structural Equation Modeling–Partial Least Squares (SEM-PLS) method using SmartPLS 4.0 software. The test results showed that all indicators met the criteria of validity and reliability. An R-square value of 0.783 indicates that CBM, OEC, and HRC are simultaneously able to account for 78.3% variation in forklift performance. The hypothesis test showed that CBM had a positive and significant effect on HEP with path coefficients of 9,225, followed by HRC of 5,999 and OEC of 4,073. These findings say that CBM is a major factor in improving forklift performance, followed by human resource competence and operational environmental conditions. This study concludes that improving condition-based maintenance strategies, developing operator capabilities, and improving the working environment in warehouses in an integrated manner can significantly and sustainably improve forklift performance.

KEYWORDS: Condition-Based Maintenance, Operational Environment Conditions, Human Resource Competency, Heavy Equipment Performance, SEM-PLS

1. INTRODUCTION

Warehouses are important parts of modern supply chains, acting as places where goods are stored, handled, and sent out. How well a warehouse works depends a lot on the material handling systems used there, and forklifts are one of the most important tools in these systems. Forklifts are used for lifting, moving, stacking, and transporting goods, so how well they work directly affects how productive the warehouse is, how quickly it can respond to customer needs, and how efficient the whole logistics system is (Jimenez et al., 2023).

Even though forklifts are very important, their performance often gets worse over time. This happens through things like more breakdowns, longer periods when the forklifts are not working, slower movement, and higher safety risks. These problems can mess up the warehouse operations, raise maintenance costs, and make the services less reliable. Studies have found that poor maintenance habits and improper use of equipment are key reasons for this decline in performance (Ng et al., 2020; Purba et al., 2018).

Forklift performance isn't just about how good the machinery is; it's also influenced by many other factors. One of the most important factors is the maintenance approach used by the company. Condition-Based Maintenance (CBM) is a forward-thinking method that uses real-time data or monitoring to decide when maintenance is needed. This helps prevent unexpected problems and makes the equipment last longer (Ali & Abdelhadi, 2022; Teixeira et al., 2020). With Industry 4.0, CBM is even better supported by predictive tools, smart sensors, and data analysis (Achouch et al., 2022; Sharma et al., 2022). However, there aren't many studies looking specifically at how CBM affects forklift performance in warehouses, especially compared to studies on manufacturing equipment.

In addition to maintenance, the environment where forklifts operate also plays a big role in their performance. Factors like the quality of the floor, how crowded the space is, lighting, temperature, air flow, humidity, and cleanliness all affect how well the forklifts work, how much wear and tear they experience, how much vibration they create, and how comfortable it is for the operator. Research has shown that factors like vibration, humidity, and environmental stress can speed up wear and tear and lower how reliable the equipment is (Huang et al., 2021; Wang et al., 2025; Xu & Grosshans, 2023). If these environmental conditions aren’t well managed, it can lead to more downtime and slower operations.

Human factors are another important part that affects how well forklifts work. Human Resource Competency (HRC) includes things like the knowledge and skills of the operators, their experience, and how safety-conscious they are. These factors play a big role in how forklifts are used and taken care of. Research in logistics and operations management shows that skilled operators help make work faster, safer, and more reliable (Aloini et al., 2022; Rafi Abdullah Shall et al., 2025). On the flip side, if operators are not well-trained, it can lead to mistakes, wrong use of equipment, and even accidents (Jimenez et al., 2023).

Even though earlier studies have looked at maintenance, environment, and human factors separately, there is not much research that brings all these aspects together into one model to understand how they affect forklift performance. Also, not many studies use advanced methods to look at how these factors work together and influence each other. Structural Equation Modeling–Partial Least Squares (SEM-PLS) is a good choice for this because it helps study complex relationships between different variables and has been used a lot in industrial engineering and maintenance research (Andhini, 2017).

Because of these gaps in research, this study looks at how Condition-Based Maintenance, Operational Environment Conditions, and Human Resource Competency affect forklift performance in warehouses. Using SEM-PLS, the study combines technical, environmental, and human factors into one model to find out which factors have the biggest impact on how well forklifts perform. The results should help add to knowledge in logistics and industrial engineering and also give useful advice for improving maintenance, managing warehouse conditions, and training operators better.

2. LITERATURE REVIEW

2.1 Heavy Equipment Performance (HEP) in Warehouse Operations

Forklifts are important tools used in warehouses to move goods around. They play a big role in how well the whole logistics system works, including how quickly things get moved and how reliable the operations are. To measure how well forklifts perform, people look at several key factors, such as how much work they can do, how often they break down, how long they're out of service when they do break, and how much it costs to keep them running. These factors help show how well forklifts help move goods inside warehouses.

Research shows that how reliable the equipment is and how well it's maintained are key to how well it performs. Studies by Kumar et al. (2020) say that when equipment isn't in good shape, it breaks down more often and isn't available as much. Corrales et al. (2020) and Ng et al. (2020) show that if equipment is down for a long time, it affects how well the whole system works. From a cost angle, Vital and Camello Lima (2020) say that good maintenance plans can cut down on costs while keeping the equipment running smoothly. These findings show that how well forklifts work depends on many things, including both the technical parts and how well they're managed.

2.2 Operational Environment Conditions (OEC)

Condition-Based Maintenance (CBM) is a way of maintaining equipment by using real-time data to check how the equipment is doing. This helps predict and prevent problems before they happen. Unlike regular maintenance that happens on a schedule, CBM is done based on how the equipment is actually performing, which makes it more accurate and efficient. Ali and Abdelhadi (2022) say that CBM helps keep equipment running more often by catching issues early, like unusual vibrations, temperatures, or pressure changes.

In industrial settings, CBM helps reduce unexpected breakdowns and makes equipment last longer. Teixeira et al. (2020) point out that CBM helps make better decisions by combining sensor data with tools that predict future problems. For forklifts, especially electric ones that work with repeated loads, CBM is especially useful because parts like batteries, electric motors, and hydraulic systems can be sensitive. Sharma et al. (2022) show that using machine learning to monitor these parts improves the accuracy of finding problems, allowing maintenance teams to act quickly.

Technology is key to making CBM work well. Using things like IoT, telematics, and real-time dashboards helps monitor equipment more quickly and accurately (Candraningtyas et al., 2025). Studies by Achouch et al. (2022) confirm that digital CBM systems help maintenance teams respond better and reduce the seriousness of problems. Because of this, CBM is widely seen as an important way to improve how well heavy equipment works in industrial environments.

2.3 Operational Environment Conditions (OEC)

Operational Environment Conditions (OEC) are the physical and environmental factors that affect how equipment works. These include things like temperature, humidity, dust levels, the quality of the floor, the layout of the warehouse, and how busy the area is with traffic. These factors can have a big impact on how stable the equipment is, how accurate the sensors work, and how much mechanical wear happens. Xu and Grosshans (2023) found that environmental conditions can mess up sensor performance and cause parts to wear out faster, especially in electric equipment.

Temperature and humidity are especially important for how well forklift batteries and electronic systems work. Wang et al. (2025) showed that high humidity can speed up the breakdown of lithium-ion batteries, making them less efficient and shortening their lifespan. Also, when dust builds up or the floors aren't clean, it can lead to sensor problems and more mechanical damage, which may cause false alarms or sudden shutdowns (Xu & Grosshans, 2023).

The quality of the floor and how the warehouse is laid out also affect forklift performance. Huang et al. (2021) found that uneven floors cause more vibration, which speeds up wear on both mechanical and electronic parts. Also, if the layout is too crowded or the aisles are too narrow, it limits how well the forklift can move around, increasing the chance of collisions and lowering productivity (Aloini et al., 2022). All these studies show that bad working conditions can lead to more maintenance needs and poorer equipment performance.

2.4 Human Resource Competency (HRC)

Human Resource Competency (HRC) refers to the technical skills, experience, training, and awareness of forklift operators and maintenance workers. How skilled these people are is very important for making sure equipment works well and stays safe. Jimenez et al. (2023) said that trained operators are more productive and have fewer incidents than those who aren't as trained.

Experience is a big part of being competent. Skilled operators are better at noticing early signs that something isn't right, like unusual vibrations or changes in battery performance. Studies by Shall et al. (2025) show that when operators are involved in daily checks, small problems don't turn into big breakdowns. Also, having structured training and certification programs helps workers follow safety rules and do preventive maintenance properly (Farezan et al., 2023).

The ability of operators and technicians to understand condition-based maintenance (CBM) data helps make maintenance more effective. When human skills match up with digital maintenance systems, the data from CBM can be used to take timely and accurate action. So, HRC doesn't just affect performance on its own it also helps make CBM systems work better.

2.5 Conseptual Framework and Hypotheses Development

Based on the reviewed literature, forklift performance is influenced by a combination of maintenance strategy, environmental conditions, and human resource competency. CBM provides proactive technical control, OEC shapes the operational context, and HRC ensures proper execution and interpretation of maintenance actions. Previous empirical findings consistently support positive relationships between these factors and equipment performance.

Accordingly, this study proposes the following hypotheses:

H1: Condition-Based Maintenance has a positive and significant effect on Heavy Equipment Performance.

H2: Human Resource Competency has a positive and significant effect on Heavy Equipment Performance.

H3: Operational Environment Conditions have a positive and significant effect on Heavy Equipment Performance.

3. METHOD

This study uses a quantitative method with a causal-explanatory design to look at how Condition-Based Maintenance, Operational Environment Conditions, Human Resource Competency, and forklift performance are connected. The goal is to find out the cause-and-effect relationships between these hidden factors using real data from warehouse activities.

To gather data, a structured questionnaire was made based on the key points of each concept and used a Likert scale for responses. The people who answered were those directly working with forklifts, such as operators, maintenance workers, and supervisors. A purposeful sampling method was used to make sure the participants had enough experience and knowledge related to the study's topics.

The data was analyzed using Structural Equation Modeling with the Partial Least Squares method (SEM-PLS) through SmartPLS 4.0 software. This method was chosen because it works well for predicting outcomes and handles complex models with several hidden factors. The analysis started with checking the measurement model to ensure the questions were valid and reliable, then moved on to the structural model to test the ideas and see how the different factors are related.

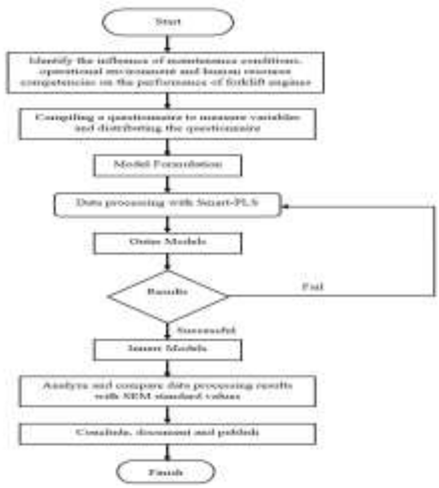

Figure. 1 Research Procedure Flowchart

Table. 1 Research Information

Variabel	Dimensi	Indikator
Heavy Equipment Performance (HEP) - (Y)	Productivity	Number of pallets/tonnage moved per forklift operation hour (Y1) (Purba, 2018)
	Downtime	Frequency of forklifts malfunctioning or stopped operation (Y2) (Kumar, 2020 dan Roysen, 2024)
	Cost Efficiency	Maintenance and repair costs for damage events (Y3) (Vital, 2020)
Condition-Based Maintenance (CBM) - (X)	Predictive Data Analytics	Accuracy rate of forklift condition analysis per operation period (X1) (Ali, 2022)
		The speed of the CBM system in responding to and detecting anomalies in forklift conditions (X2) (Amali, 2025)
	Proactive Maintenance Measures	Effectiveness of treatment measures taken before damage occurs (X3) (Ali, 2022)
		The number of preventive measures taken based on the results of CBM analysis (X4) (Ali, 2022)
	Supporting Technology	Constraints of CBM (sensors, telematics, IoT) technology used (X5) (Candraningtyas, 2025)
		Speed and precision of technology in presenting forklift condition data (X6) (Sharma, 2022)
Operational Environment Conditions (OEC) - (Z1)	Operational Environment	Temperature and humidity in the warehouse area (Z11) (Xu, 2022)
	Work Area Condition	Surface quality of warehous flooring (Z12) (Wang, 2025)
		Difficulty level of forklift layout and work area density (Z13) (Huang, 2021)
HR Competence (HRC) - (Z2)	Technical Competence	The level of understanding of the operator/technician of the forklift CBM system (Z21) (Jimenez, 2023)
		Frequency of operator training related to forklift operation and maintenance (Z22) (Farezan, 2023)
	Work Experience	Length of operator/technician experience in handling forklifts (Z23) (Shall, 2025)
		Operator/technician's ability to analyze data from the V+CBM system (Z24) (Shall, 2025)

4. RESULTS AND DISCUSSION

4.1 Outer Model Measurements

The *measurement of the outer model* is the first step taken. By using *Smart-PLS* 4.0, the results of the *outer model* with reflective indicators as shown in Figure 2 were obtained.

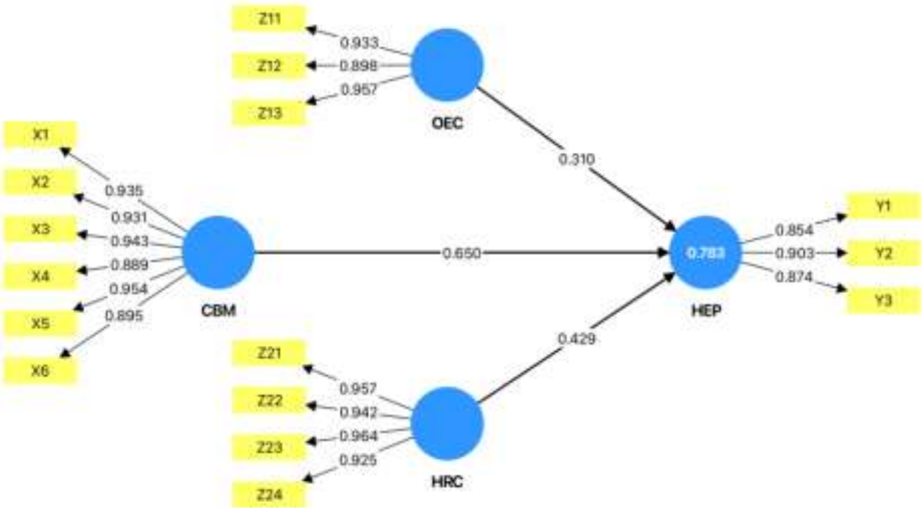

Figure 2. Outer Model for CBM, OEC and HRC

Based on the results of the outer model measurements above, it is found that the value of the Loading Factor of each indicator is as shown in the table below

Table. 2 Loading Factor for Condition-Based Maintenance Variables

Indicator	Loading Factor	Remarks
X1	0.935	Valid
X2	0.931	Valid
X3	0.943	Valid
X4	0.889	Valid
X5	0.954	Valid
X6	0.895	Valid

Table. 3 Loading Factor untuk Variabel Operational Environment Conditions

Indicator	Loading Factor	Remarks
Z11	0.933	Valid
Z12	0.898	Valid
Z13	0.957	Valid

Table. 4 Loading Factor for Human Resource Competency Variables

Indicator	Loading Factor	Remarks
Z21	0.957	Valid
Z22	0.942	Valid
Z23	0.964	Valid
Z24	0.925	Valid

Table. 5 Loading Factor for Variable Heavy Equipment Performance

Indicator	Loading Factor	Remarks
Y1	0.854	Valid
Y2	0.903	Valid
Y3	0.874	Valid

Based on the Loading Factor of each variable, the value is above 0.7, so it can be concluded that the standardized correlation between the indicator and the latent variable is said to be valid.

Furthermore, after knowing that the value of the outer model is valid, Reability and Validity tests are carried out to determine the consistency of the indicators in measuring a latent construct. The values obtained are as shown in Table. 6 below.

Table. 6 Validity & Realibility Test

Variable	Cronbach's Alpha (CA)	Composite Reliability (CR)	Average Variance Extracted (AVE)	Remarks
CBM	0.966	0.973	0.855	*Reliable*
HEP	0.850	0.909	0.769	*Reliable*
HRC	0.962	0.972	0.897	*Reliable*
OEC	0.921	0.950	0.864	*Reliable*

From the table above, it can be seen that Cronbach's Alpha (CA) and Composite Reliability (CR) values are greater than 0.70. This also applies to the Average Variance Extracted (AVE) value that is more than 0.50. Thus, it can be concluded that all indicators in this study have met the reliability and validity standards of construction. This means that each indicator is able to measure the variables in question consistently and accurately. In addition, these results show that the research instrument is trustworthy, relevant, and feasible to use in the next stage of analysis because it shows stable and significant measurement capabilities against the variables under study.

Then conduct a Discriminant Validity test to measure the extent to which a construct is empirically different from other constructs. There are two methods that can be used. First, the Fornell-Larcker Criterion where the root value of AVE (diagonal) must be greater than the correlation between constructs. From the results obtained from the Fornell-Larcker Criterion, all AVE diagonal correlations are greater than the correlations between constructs, meaning that all constructs have a fairly good discriminant validity as shown in Table. 7 below.

Table. 7 Criteria Fornell Larcker

	CBM	HEP	HRC	OEC
CBM	0.925			
HEP	0.655	0.877		
HRC	-0.058	0.479	0.947	
OEC	0.095	0.493	0.283	0.930

Second, the Heterotrait-Monotrait Ratio where the Discriminant Validity is fulfilled when the HTMT value is <0.90 where the test results show an HTMT value of <0.90 as seen in Table. 8 following.

Table. 8 Ratio Heterotrait-Monotrait

	CBM	*HEP*	*HRC*	*OEC*
CBM				
HEP	0.717			
HRC	0.091	0.527		
OEC	0.105	0.551	0.302	

4.2 Inner Model

Structural model evaluation can be carried out by testing the Determination and R^2 Effect Size F^2coefficients. Based on the results of the R-Square measurement as seen in Table 9, it can be known the extent of the contribution of the free variable to the bound variable in the developed model is known.

Table. 9 R-Square

	R-square	R-square Adjusted
HEP	0.783	0.769

Based on the table above, the HEP (Heavy Equipment Performance) value is 0.783. This means that the variables CBM (Condition-Based Maintenance), OEC (Operational Environment Conditions), and HRC (Human Resource Competency) together affect Heavy Equipment Performance by 78.3%. The rest, which is 21.7%, is influenced by other factors that are not included in this research model. These results show that the structural model used is quite good in explaining the relationships between variables, so it can be considered relevant and significant in showing variations in Heavy Equipment Performance.

F-Square value F^2. used to determine the influence of the predictor variable (X) on the dependent variable (Y). The value of F-Square ranges from $0.02 \leq F2 < 0.15$ which indicates the variable has a weak influence, $0.15 \leq F2 < 0.35$ which indicates the variable has a moderate influence, and $F2 \geq 0.35$ which indicates the variable has a strong influence. Based on the measurement results F^2 as seen in Table. 10, it is known that Condition-Based Maintenance, Operational Environment Conditions and Human Resource Competency have a strong influence on Heavy Equipment Performance. It is based on the value of each indicator > 0.35.

Table. 10 F-Square

	F-square
CBM⇒HEP	1.919
HRC⇒HEP	0.775
OEC⇒HEP	0.402

4.3 Calculate Bootstrapping

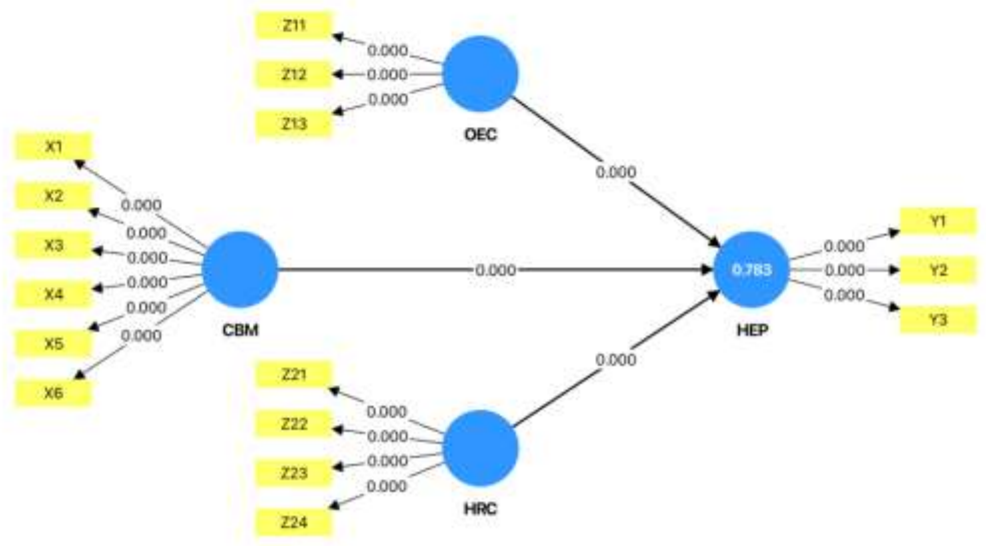

Figure. 3 SEMPLS Version 4 Results - Bootstrapping Research Model

The next test was carried out by checking the significance, namely by looking at the value of the parameter coefficient and t-statistics to ensure that the relationship between variables was indeed statistically influential. In the bootstrapping algorithm stage, the Path Coefficients method is used to find out how much of a direct influence of each exogenous variable is on the endogenous variable. The results of the analysis can be seen in detail in Table 4.11, which shows the magnitude of the influence and direction of the relationship between variables in this research model. However, before that, a model suitability test was carried out to see if the overall PLS model was suitable (fit) with the data. In Table 4. 10 it is known that the SRMR (Standardized Root Mean Square Residudual) value of 0.059 is below the limit of 0.08, so it can be concluded that the research model has a good degree of suitability. An NFI value of 0.857 also indicates that the model has met the eligibility criteria.

Tabel. 11 Model Fit Test

	Saturated Model	Estimated Model
SRMR	0.059	0.059
d_ULS	0.475	0.475
d_G	0.502	0.502
Chi-square	134.916	134.916
NFI	0.857	0.857

Tabel 4. 1 Path Coefficients

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
CBM⇒HEP	0.650	0.650	0.070	9.225	0
HRC⇒HEP	0.429	0.433	0.071	5.999	0
OEC⇒HEP	0.310	0.315	0.076	4.073	0

Based on Table 4. 11 It can be seen that the results of the significance test show a strong and consistent relationship between exogenous variables and endogenous variables in this study model. Broadly speaking, each indicator that is analyzed concludes that based on the Hypothesis, accept H1 and reject H0. The explanation of the influence of each variable is as follows:

1. Effect of CBM on HEP

The test results showed that CBM had a positive and significant impact on HEP. A path coefficient value of 0.650 indicates that if the CBM increases, then the HEP will also increase in the same direction. The magnitude of this coefficient value implies that CBM is the main factor influencing HEP compared to other variables in the model.

A statistical t-value of 9.225, which is much greater than the critical limit of 1.96, as well as a p-value of less than

0.001, proves that the influence of CBM on HEP is statistically significant. In addition, the similarity between the Original Sample (0.650) and Sample Mean (0.650) values indicates that the model is stable and consistent in the bootstrapping process.

In terms of meaning, these results show that CBM has an important role in increasing HEP. In other words, the better the implementation or condition of CBM, the performance or achievement of HEP will increase significantly.

From the test results, it was found that indicators such as prediction analysis accuracy (X1) and proactive action effectiveness (X3) had a very high validity value in supporting the CBM variable. Effective CBM implementation allows proactive maintenance actions to be carried out early, thus preventing high downtime, extending equipment life, and reducing unnecessary repair costs.

2. Effect of HRC on HEP

The HRC variable turns out to have a good and important influence on HEP. The path coefficient is 0.429, which means that the increase in HRC actually improves the HEP, although the level of influence is not as great as the CBM.

A statistical t-value of 5.999 with a p-value of less than 0.001 indicates that the relationship between HRC and HEP is statistically significant. The very small difference between the Original Sample (0.429) and the Sample Mean (0.433) shows that the results of these estimates are quite accurate and unbiased.

In terms of concept, these results show that HRC is an important supporting factor in increasing HEP. This means that by strengthening the aspects included in HRC, there will be a positive impact on HEP, even though the effect is not as big as CBM.

Work experience (Z23) and the level of operator understanding of the system (Z21) are the strongest indicators that support human resource competence in maintaining machine performance. Technical training and operator compliance with the Daily Check-Up (P2H) can significantly reduce the number of breakdowns and operational disruptions.

3. Effect of OEC on HEP

The results of the analysis also showed that OEC had a positive and significant effect on HEP, with a path coefficient of 0.310. This figure shows that OEC contributes to HEP, although its influence is not as great as the CBM and HRC.

The t-statistical value of 4.073, which is higher than the threshold of 1.96, as well as a p-value below 0.001, proves that the influence of OEC on HEP is indeed statistically significant. The consistency between the original sample value (0.310) and the sample average (0.315) showed that the estimated results were quite stable.

Substantially, this suggests that OEC plays a supporting role in increasing HEP. Although its influence is not as strong as other variables, OEC still makes an important contribution and should not be ignored in the research model.

The difficulty level of the layout and the density of the work area (Z13) as well as temperature and humidity (Z11) are key indicators in assessing the influence of the operational environment. Poor working environments, such as uneven floors, can increase mechanical vibrations that accelerate component wear. On the contrary, an optimal warehouse layout supports smooth maneuvering and transport productivity.

5. CONCLUTION

The results of this study state that the three variables, Condition-Based Maintenance (CBM), Operational Environment Condition (OEC) and Human Resource Competence (HRC) have a positive effect on Forklift Performance – Heavy Equipment Performance (HEP). However, of the three variables, the most significant is CBM.

So that to get maximum performance on forklifts in warehouse management, a good maintenance strategy is needed and made a top priority in order to increase productivity, reduce the risk of downtime and reduce unnecessary repair costs. Then followed by paying attention to the environment and working operational conditions and the competence of the forklift operator.

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