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Research Article

The Effect of Condition-Based Maintenance on Heavy Equipment Performance in the Coal Mining Industry: The Moderating Roles of Operational Environmental Conditions and Human Resource Competency

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ABSTRACT

Heavy equipment performance is an important factor that can affect productivity factors in the Indonesian coal mining sector. A major reason behind the high downtime is because they follow time-based maintenance (TBM) methods on their heavy equipment. This has led to the search of new and much better and effective methods such as Condition-Based Maintenance (CBM) method. The use of CBM as a predictive maintenance methodology by coal industry players to minimise equipment downtime is proliferating but, at present, little evidence exists regarding how operational environmental conditions and human resource competencies impact the effectiveness of CBM. This study investigates the impact of Predictive Data Analysis (PDA), Maintenance Actions Proactive (MAP) and Supporting Technology (STE) on heavy equipment performance (HEP) and which include Operational Environment Conditions (OEC) and Human Resource Competency (HRC) as moderating variables. This study collected data from 207 operational and maintenance personnel in Indonesian coal mining companies that have adopted CBM. Analysis of data was conducted through Partial Least Squares Structural Equation Modeling (PLS-SEM) using Smart-PLS 4.0 software. The results showed that PDA, MAP, and STE were positively related to heavy equipment performance, with MAP showing the strongest relationship among the three CBM dimensions. OEC and HRC also had a significant direct effect on performance. However, among the proposed moderating relationships, only the interaction between HRC and MAP was statistically significant. These findings suggest that CBM effectiveness is influenced not only by maintenance-related practices but also by workforce capabilities. This study provides empirical evidence on the relationship between CBM implementation, operational conditions, human resource competencies, and heavy equipment performance in the context of coal mining operations.

Keywords: Condition-Based Maintenance, heavy equipment performance, equipment downtime, predictive data analysis, human resource competency

INTRODUCTION

With demand for raw materials on the rise, combined with price fluctuations and increased operating costs, mining companies are being driven to enhance operational efficiency and equipment reliability. Availability of equipment is directly related to continuous production and maintenance costs, therefore reducing unplanned downtimes becomes an operational issue. As the world's third largest coal producer of around 775 million tons in 2023 [1], the Indonesian coal industry faces major challenges in achieving production targets that are increasing every year, encouraging mining contractors to prioritize operational efficiency by improving the performance of heavy equipment. To achieve this, one of the most important factors is the performance (reliability) of the heavy equipment being operated. The performance of heavy equipment in the coal mining industry is a crucial factor that directly affects the productivity and efficiency of mining operations. The results of previous studies consistently demonstrate that one of the company's operations is performed by its heavy equipment and such performance remains under control when it comes to mining performances, in addition to availability, reliability, effective maintenance practice directly influencing overall effectiveness operation [2]–[4]. From an empirical perspective, insufficient equipment effectiveness noticeably limits the mine output by lowering calendar system availability and equipment utilization and simultaneously increasing production loss and coal quality issue in coal mining operation [3],[4].

These circumstances are reflected in documented cases of heavy equipment downtime in coal mining operations, where equipment failures have been associated with production delays, reduced equipment availability, and increased maintenance costs [4],[5]. For instance, unplanned power shovel breakdowns have been recognized as an important contributor to operational disruptions at multiple mining sites where production continuity and maintenance efficiency are affected [4]. These results could not only confirm a continuing significant failure issue in the area of better equipment reliability, but also that more proactive maintenance initiatives are warranted. Historically, the coal industry has used Time-Based Maintenance (TBM) to monitor heavy equipment. Yet, there is growing literature that emphasizes the failure of TBM in dealing with unforeseen failures particularly in highly varied and hostile mining environments. Syamsundar said, TBM only cuts the probability of sudden failure by approximately 30% as shown in [6]; showing little protectiveness to prevent unexpected collapses. This increasing awareness of the shortcomings of TBM has been associated with a switch in paradigm towards the use of real-time condition monitoring for decision making on maintenance and equipment reliability in mining.

CBM is a maintenance method that utilizes IoT sensors and predictive analytics to monitor equipment conditions in real-time, which allows CBM to be more proactive and has the potential to become a data-based maintenance method solution [7]. CBM is one of the predictive maintenance methods (PdM-Predictive Maintenance) that works based on degradation status information provided by IoT-online monitoring technology (real-time data). With the ability to classify different types of machine downtime in real-time, the system can plan timely maintenance actions, reduce machine failures and minimize unplanned downtime [8]. However, challenges remain, such as the need for an integrated data management system and high-capacity storage to process the large amount of data generated by these IoT devices in mining operations [9]. Theoretically, CBM is designed to detect potential problems before serious failures occur [10]. In a mining environment, CBM is expected to be able to reduce downtime by detecting problems before heavy equipment experiences major damage. Research by H. Meriem et al. [11] and S. Elkateb et al. [12] explains that predictive maintenance systems that utilize IoT devices and machine learning algorithms have significant potential to improve the efficiency and productivity of heavy equipment. CBM can effectively minimize risks and reduce maintenance costs by ensuring integrated system reliability and availability [13], [14] and [15]. CBM has emerged as a transformative approach in heavy equipment management, particularly in the coal mining industry, where operational efficiency and equipment reliability are critical [16], [17]. Recent advances in technologies such as Caterpillar's MineStar™ and Komatsu's Komtrax demonstrate the potential of CBM to minimize unplanned downtime [18], [19].

Condition-Based Maintenance (CBM) has been widely discussed in recent maintenance and reliability research. Nevertheless, much of this literature remains centered on technological development [20], [21]. For example, Sharma et al. [21] reviewed CBM applications from the perspectives of machine-learning techniques, predictive accuracy,

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and model interpretability, while Wang et al. [22] developed a CBM framework based on remaining useful life prediction and maintenance-delay optimization for multicomponent systems. Similarly, Elkateb et al. [12] proposed an IoT- and machine-learning-based predictive maintenance architecture aimed at improving monitoring and failure prediction capabilities in industrial environments. While these studies provide important advances in CBM technology, their primary concern lies in improving prediction models and maintenance decision support systems. Less attention has been given to the operational context in which CBM is implemented, particularly whether environmental operating conditions and differences in workforce competency influence the extent to which CBM improves equipment performance. As a result, the boundary conditions under which CBM produces superior operational outcomes remain insufficiently explored, especially in heavy-equipment-intensive industries such as coal mining. This exclusion is a critical limitation since mining sites tend to have harsh conditions and rely heavily on technicians for expertise, which may affect the practical use of even advanced CBM systems despite their favorable analytical performance. The fact is that advanced CBM technology places high demands on the skill and technical ability of involved instrument technicians and operators. Analog technology included the decoding of data from the CBM system. Proper interpretation of data provided by the system is a prerequisite for timely and accurate implementation of maintenance actions. Poor competence level influences interpretation of data, and inability to take quick and well-inquired decision hence the loss of potential return on using CBM for enhancing heavy equipment performance. In order to optimize the performance of the heavy equipment, a variety of factors that influence the effectiveness of heavy equipment maintenance system need to be analyzed.

Organizational and managerial factors can clearly impact CBM performance, but by limiting the factors to those that directly relate to the maintenance execution process in mining operations, such as operational environmental conditions and human competence. The coal mining domain has some of the most extreme and inconsistent operating environments contributing various types of data noise affecting equipment condition monitoring/maintenance outcome including dust exposure, vibration, humidity, and variable geological conditions [23-26]. It has also been pointed out that the interpretation of diagnostic information into proper maintenance actions is largely dependent on the ability of human maintenance personnel, and hence easy and timely execution of CBM needs to be facilitated [22]. Prior research on mining systems has also identified environmental monitoring and workforce capability as crucial determinants of maintenance outcomes [7], [23]. As both aspects relate to day-to-day equipment operation under difficult field conditions, where human expertise is a critical factor in maintenance decisions, these two dimensions were perceived as more immediate and operationally relevant compared with the level of organizational variables in Indonesian coal mines. H. N. Teixeira [27] verify CBM, being able to predict timely intervention yet not explore how favourable or unfavourable the effect of environment and workforce skill can be increased/decreased. This gap is particularly relevant in the Indonesian coal mining sector, where heavy equipment frequently operates under demanding environmental conditions characterized by high rainfall, elevated humidity, extreme temperatures, and challenging terrain, all of which can influence equipment condition, maintenance requirements, and operational reliability [28]. At the same time, the increasing adoption of digital monitoring systems, predictive analytics, and data-driven maintenance practices has intensified the need for personnel capable of interpreting equipment-condition information and converting it into appropriate maintenance actions [22], [27].

These operational environmental conditions and HR competencies are moderator variables that greatly influence the relationship between CBM and heavy equipment performance, because heavy equipment operated in extreme conditions requires a more adaptive maintenance strategy and adequate HR competencies. In addition, although technologies such as the Internet of Things (IoT) and machine learning have expanded the capabilities of CBM, the application of this technology in mining environments still faces major challenges, especially the influence of extreme environments and the ability of HR to operate it. Research on the effect of CBM implementation on heavy equipment performance in the coal mining industry is motivated by the 2 conditions above. This study therefore aims to empirically determine the extent to which operational environmental conditions and human resource competency moderate the relationship between Condition-Based Maintenance (CBM) implementation and heavy equipment performance through an integrative SEM-PLS model.

This study contributes both theoretically and practically to the CBM literature. Theoretically, it adds to existing CBM literature by using operational environmental conditions and human resources competency as the moderating variables on the connection between implementing CBM and heavy equipment performance. Although previous studies have largely paid attention to the technology and forecast dimensions of CBM, we show here that performance evidence for CBM may hinge on operational context and employee competence. This research addresses this gap by integrating these contextual variables into one empirical framework in order to provide an improved understanding of the effectiveness of CBM for mining operations. Practically, the proposed model theoretically serves as a structuring mechanism enabling management of maintenance technology deployment to environmental reality and workforce capability in order to better decision-making around the appropriateness of maintenance and ultimately equipment performance.

METHODS

Data collection technique

The questionnaire items were developed based on a literature review of the previous studies related to Condition-Based Maintenance, maintenance management, operational environmental conditions, human resource competency and heavy equipment performance. The initial measures were taken from validated instruments and then modified to better align with the operational characteristics of coal mining endeavors. To assess content validity, the preliminary questionnaire was evaluated by 5 experts consisting of two maintenance engineers, one CBM specialist, and two industrial engineering academics. They were asked to assess the relevance, clarity, and suitability of each item for the intended construct. Based on their feedback, several statements were revised to improve wording clarity and reduce ambiguity. Before the main survey, a pilot test involving 30 respondents with operational and maintenance responsibilities similar to those of the target population was conducted. The pilot study was intended to examine item clarity, questionnaire comprehensibility, and internal consistency. Items that generated respondent confusion or showed weak consistency during the preliminary assessment were refined prior to full-scale data collection. The final version of the questionnaire was then administered to the study respondents. The eventual form of the questionnaire made use of a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree), as suggested by the reflective measurement theory in PLS-SEM and convenient to weather changes in CBM implementation and equipment performance.

Population and Sample

The present work analyses the impact of CBM on performance of heavy equipment in coal mines where environmental condition in operation together with competency of human resource were considered as moderating factors. Purposive sampling was employed to select coal mining companies that had implemented Condition-Based Maintenance (CBM) in their maintenance operations. The participating companies were selected based on two criteria: (1) the formal adoption of CBM practices and supporting monitoring systems, and (2) the willingness to provide access to operational and maintenance personnel directly involved in CBM implementation. The unit of analysis consisted of supervisors, engineers, maintenance personnel, and equipment operators who possessed practical experience with CBM activities.

Of the 959-coal enterprise in Indonesia, CBM application is only practiced by only about 5% of large and medium-scale companies that is about 48 enterprises. This study was conducted in five mining companies that have adopted CBM. The companies served as research sites, while the unit of analysis was the individual employee. Eligible respondents included operational and maintenance personnel directly involved in equipment monitoring, condition assessment, maintenance planning, inspection activities, and maintenance execution within the CBM system. This selection criterion was applied to ensure that respondents possessed adequate knowledge and practical experience regarding CBM implementation.

The required sample size was determined based on the structural model complexity rather than a general rule-of-thumb. Following recommendations for PLS-SEM, the minimum sample requirement was assessed with reference to the largest number of structural paths directed toward an endogenous construct in the proposed model. Heavy Equipment Performance, as the main endogenous construct, received direct effects from CBM dimensions, Operational Environmental Conditions, Human Resource Competency, and two interaction terms representing the moderating effects. According to Prabowo, et al. [29] and Hair et al. [30], the minimum sample size for the SEM method is 5-10 times the number of indicators. In this study, there are 17 indicators multiplied by 10 = 170, so the minimum sample size of 170 respondents is considered sufficient at a significance level of 0.05 [29], [30]. The final dataset consisted of 207 valid responses, exceeding the minimum requirement and providing adequate statistical power for estimating both direct and moderating effects. Individual level data were collected and analysed as the study is perception-based academic research on employees towards CBM implementation, operational environmental conditions, human resource competency and heavy equipment performance. No data was aggregated to company level, nor was the study comparing participating companies. Consequently, the PLS-SEM analysis was performed using individual-level observations, with each respondent treated as an independent source of information concerning CBM practices and equipment performance within the operational environment in which they worked.

Variables, Dimensions and Indicators

There were 6 variables involves in this study, namely:

1. Dependent Variable: Heavy Equipment Performance (Y)
2. Independent Variable: Condition-Based Maintenance – CBM (X), CBM have 3 sub-variables namely:
    a. Predictive Data Analysis - X1: Use of analytical techniques to predict potential damage or maintenance based on collected data.
    b. Maintenance Actions Proactive - X2: Implementation of maintenance before damage occurs based on monitoring and analysis results.
    c. Supporting Technology - X3: Use of technology such as IoT and AI to support effective CBM implementation.
3. Moderator Variables (Z) namely:
    a. Operational Environmental Conditions - Z1: Environmental and operational factors such as temperature, humidity and workload that can affect the effectiveness of CBM.
    b. Human Resource Competency - Z2: Level of knowledge and skills of personnel in operating and utilizing the CBM system.

Table 1 summarizes variables, dimensions and indicators based on the research conceptual model. All constructs were measured using a five-point Likert scale ranging from 1 (“very low”) to 5 (“very high”). Respondents were asked

Table 1. Research Variables, Dimensions and Indicators

Variables	Dimensions	Indicators
Heavy Equipment Performance (Y)	Productivity	• Amount of coal produced per work shift (Explanation: the amount of coal produced per work shift is treated not as a measure of labor productivity, but as a direct manifestation of the effectiveness and reliability of equipment in a machine-intensive production system) • Production target achievement
	Downtime	• Frequency of heavy equipment downtime • Average duration of downtime per incident
	Cost Efficiency	• Maintenance costs per equipment in one month of operation • Reduced Total maintenance cost
Condition-Based Maintenance (CBM) (X)	Predictive Data Analysis (X1)	• Accuracy of predictive analysis results for potential damage • The role of Predictive analysis in reducing HE downtime • Predictive analysis supporting decision making in maintenance problem • Speed of analysis response in detecting problems
	Maintenance Action Proactive (X2)	• Effectiveness of maintenance actions based on equipment conditions • Number of preventive actions taken based on analysis results • Proactive maintenance reduced HE's failures frequency
	Supporting Technology (X3)	• Reliability of technology • Accuracy and speed of technology
Operational Environment Conditions (Z1)	Operational Environment	• Dust level at the operating location • Pollutant level in the operating location • Temperature at the operating location
	Terrain Conditions	• Difficulty level of the operating terrain
HR Competence (Z2)	Technical Competence	• Technician understanding of the CBM system • Frequency of training related to condition-based maintenance
	Work Experience	• Technician work experience in the field of heavy equipment maintenance • Technician ability to analyze data from the CBM system

to provide a rating based on their observation and experience in the last six months of equipment operation. The directions included at the beginning of the questionnaire were standardized to minimize respondents interpreting measurement items differently across operational sites and job functions.

Some indicators of operational and environmental conditions that typically recur in mining operations were assessed from the perspective of structured responses rather than company records. For the indicator "amount of coal produced per work shift", respondents were asked to rate whether the equipment or event they were responsible for achieved the production target expected on a typical shift. The average duration of downtime per incident is defined in terms of the average time length associated with equipment stoppages due to breakdowns or operational failures. Respondents were asked to rate the relative level of maintenance costs related to the equipment as a "monthly operating cost aversive."

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Environmental-condition indicators were also considered using three perception-based assessments. The variables for 'level of dust at the working place' and 'temperature at the working place', respectively, measured how often workers experienced dust/loud noise during day-to-day work as well as the frequency of severe exposure in their work environment. A score of 1 indicated rare occurrence or mild intensity, while a score of 5 indicated high occurrence or strong intensity for each indicator. This operationalization was intended to provide a common basis for evaluation among respondents working in different mining locations while maintaining consistency with the perceptual measurement approach adopted in this study

Relationship Between Variables

Direct Influence:

1. X1→Y: Predictive data analysis helps in planning timely maintenance, thereby increasing machine reliability and productivity. Predictive maintenance, a core component of CBM, has been shown to enhance equipment reliability and reduce lifecycle costs by enabling early intervention based on sensor-driven prognostics and health assessment of machinery [31, 32]
2. X2→Y: Proactive maintenance actions prevent serious damage and reduce downtime and maintenance costs. Proactive maintenance actions prevent severe component damage and reduce downtime and maintenance costs by enabling timely interventions based on actual equipment condition rather than fixed schedules, thereby improving reliability and operational availability [33, 34].
3. X3→Y: The use of supporting technology increases accuracy and efficiency in the CBM process, having a positive impact on machine performance. The use of supporting technology enhances accuracy and efficiency in the CBM process by enabling real-time condition monitoring and reliable diagnostics, which positively affects machine performance and operational reliability [35, 36].

Moderator Variables:

1. Z1 moderates between X and Y: Operational environmental conditions can strengthen or weaken the influence of CBM on heavy equipment performance.
2. Z2 moderates between X and Y: HR competency determines how CBM is implemented and impacts heavy equipment performance.

Figure 1 presents the proposed SEM model to see the relationship between the variables to be studied.

Research Hypotheses

There were 11 hypotheses that had been tested namely:

- Hypothesis 1 (H1): Predictive Data Analysis (X1) has a significant positive effect on Heavy Equipment Performance (Y). Predictive data analysis enables maintenance personnel to identify early signs of equipment deterioration and estimate potential failures before breakdowns occur. Equipment availability improves through timely maintenance intervention and unplanned downtime is reduced. As discussed, previous works report that predictive analytics and condition-monitoring systems lead to well-planned maintenance and enhanced equipment reliability, which in turn integrates operational performance [12], [21], [37].
- Hypothesis 2 (H2): Maintenance Actions (X2) have a significant positive effect on Heavy Equipment Performance (Y). Condition monitoring keeps track of the equipment health and operating status continuously. With accurate monitoring, maintenance can be performed based on the actual condition and need of equipment rather than at fixed intervals reducing failure risk and helping maintain smooth operation of the equipment. Previous literature

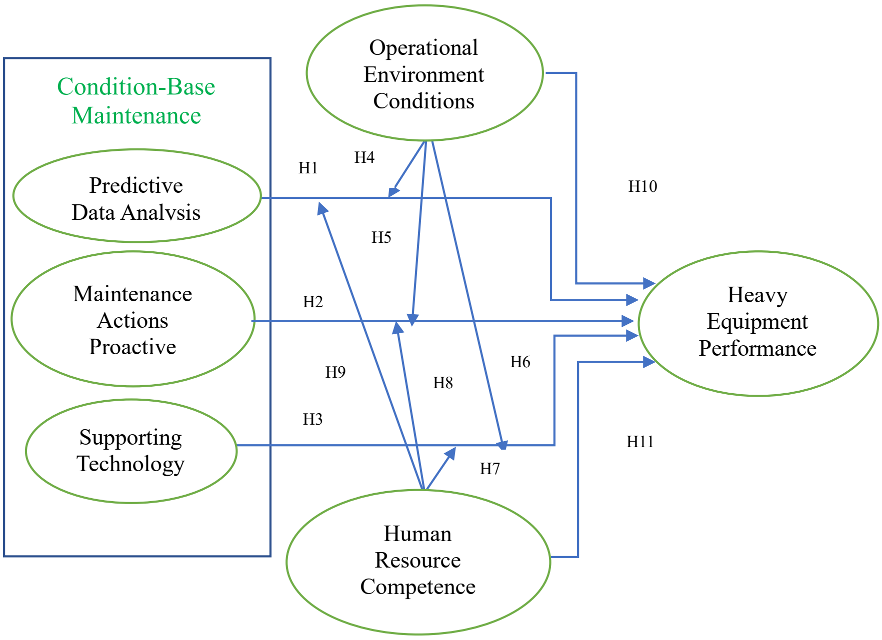

Figure 1. Research Conceptual Model proposed by Authors

suggests that good condition-monitoring practices are correlated with (I) higher a reliability and maintenance effectiveness [2], [22],[38].

- Hypothesis 3 (H3): Supporting Technology (X3) influences Heavy Equipment Performance (Y) positively and significantly. The success of CBM relies on supporting technologies for data acquisition, transmission, storage and analysis. The right technology infrastructure helps to facilitate better maintenance-decisions and makes the actual maintenance action more physically responsive, which promotes better overall equipment performance [12], [21], [39].
- Hypothesis 4 (H4): Operational Environmental Conditions (Z1) moderate the relationship between Predictive Data Analysis (X1) and Heavy Equipment Performance (Y) [25].
- Hypothesis 5 (H5): Operational Environmental Conditions (Z1) performs moderation in the relationship between Maintenance Actions (X2) and Heavy Equipment Performance (Y) [40]
- Hypothesis 6 (H6): Z1 moderates the relationship between X3 and Y – The role of Supporting Technology. [40].
- Hypothesis 7 (H7): The Competence HR (Z2) moderating towards Supporting Technology (X3) and Heavy Equipment Performance (Y) [41].
- Hypothesis 8 (H8): HR Competency (Z2) moderates the relationship between Maintenance Actions (X2) and Heavy Equipment Performance (Y). The impact that CBM provides will differ from one operating environment to the other. Element such as, dust and temperate that vary too much or are happened too frequently, humidity, hilly terrain influences the reliability of sensors & instruments with varied wear rates. Accordingly, the application of CBM to enhance equipment performance potentially varies with the environmental conditions which exist during working [7], [23], and [42].
- Hypothesis 9 (H9): HR competency (Z2) moderate through Predictive Data Analysis(X1) to Heavy equipment performance(Y). CBM generates value not just from technology, but through the humans who interpret data and make maintenance decisions. Improved technical knowledge and maintenance competence allow organizations to make more use of the information generated for CBM, enhancing its potential contribution to equipment performance [21], [22], [43]

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- Hypothesis 10 (H10): Environmental Operational Conditions (Z1) directly affect significantly positive and Heavy Equipment Performance(Y). It is well-known that operational conditions such as exposure to dust, temperature variation, humidity, terrain characteristics and operating loads affect the wear of equipment, failure occurrence and maintenance frequency. Existing studies found that equipment reliability and operational performance tend to deteriorate when operating environments are adverse. Consequently, in addition to acting as a moderator, operational environmental conditions are predicted to have a direct impact on Heavy Equipment Performance [6], [26], [40].
- Hypothesis 11 (H11): HR Competence (Z2) can directly influence Heavy Equipment Performance (Y). How well equipment operates and how efficient maintenance processes are depend heavily on the technical knowledge, diagnostic ability, and hands-on experience of maintenance personnel and equipment operators. With higher skill levels, accurate fault location, timely maintenance actions, and better usage of equipment resources. Therefore, HR Competency is assumed to have a positive direct effect with respect to Heavy Equipment Performance [41], [42], [43]

Data Analysis Techniques

Data analysis methods are an integral part of quantitative research in the processing, analysis and interpretation of acquired data. The study uses a method for tentative hypothesis testing and role play of the predictors. The choice of PLS-SEM is because it is an appropriate analytic procedure for modelling complex predictive relationships with direct and moderating effects between them, while imposing minimal distributional assumptions. Data analysis was conducted utilizing Smart-PLS 4.0. Path-weighting model estimation with a maximum of 300 iterations and a stop criterion of 10^{-7}. We started the assessment of measurement model with indicator reliability, internal consistency reliability, convergent validity, and discriminant validity. The structural model was subsequently assessed using path coefficients, coefficient of determination (R^2), effect size (f^2), and predictive relevance (Q^2). Statistical significance was examined through a bootstrapping procedure with 5,000 resamples at a 95% confidence level. Moderating effects were tested using the two-stage approach available in Smart-PLS. In the first stage, latent variable scores were obtained for each construct. In the second stage, interaction terms were generated by multiplying the latent variable scores of the predictor and moderator constructs. These interaction constructs were then incorporated into the structural model and estimated together with the direct effects. The significance of moderation was evaluated based on bootstrapped path coefficients, t-values, and p-values, while the magnitude of the moderation effect was assessed using effect size (f^2) and changes in the explained variance (R^2) of the endogenous construct.

Validity Test

The validity test encompassed both convergent and discriminant validity to ensure the soundness of the measurement model. Convergent validity focuses on how strongly the indicators associated with a particular variable relate to one another, and it was assessed using the Average Variance Extracted (AVE). In this context, AVE values exceeding 0.5 were taken to indicate adequate convergence among the indicators, confirming that they meaningfully reflect the intended construct [29],[30].

Discriminant validity was applied to confirm that each variable remains distinct rather than overlapping with others. This involved comparing the AVE of each variable with its correlations with other variables, ensuring that a construct shares more variance with its own indicators than with external ones. The evaluation followed the Fornell–Larcker criterion and cross-loading analysis. Specifically, the square root of the AVE for each construct needed to exceed its correlations with all other constructs in the model, signaling that it better explains its own measures than those of different constructs. At the same time, each indicator was expected to show its highest loading on the construct it was designed to measure compared to its loadings on other constructs. When these two conditions were met, discriminant validity was regarded as adequately established.

Reliability Test

The reliability test was conducted to ensure the internal consistency of each variable, relying on two widely accepted measures: Composite Reliability (CR) and Cronbach's Alpha. These indicators provide a clear picture of how consistently the items within a construct work together in capturing the same underlying concept. In practice, both CR and Cronbach's Alpha serve as benchmarks for assessing whether the measurement items produce stable and dependable results across different observations. Values exceeding the threshold of 0.7 are generally interpreted as evidence of good reliability, reflecting a satisfactory level of consistency among the indicators. When this standard is met, it suggests that the construct is measured with sufficient precision and coherence, thereby strengthening the overall credibility of the research findings [29],[30],[34].

Testing the Measurement Model

The measurement model was designed to examine how latent variables are reflected through their corresponding indicators, ensuring that each construct is properly represented. This process involved several key steps. First, construct validity and reliability were assessed by examining the loading factors of each indicator, as these values indicate the strength of the relationship between an indicator and its underlying variable. An indicator was considered acceptable when its loading factor exceeded 0.7, signaling that it contributes meaningfully to the construct it represents [29], [30], [44]. In addition, the Average Variance Extracted (AVE) was calculated to verify that each latent variable is capable of explaining a sufficient portion of variance in its indicators, reinforcing the adequacy of the measurement model as a whole.

Structural Model Testing

Once the measurement model had been confirmed, the analysis moved to the structural model to examine how the latent variables relate to one another within the conceptual framework. This stage focused on several key evaluations. Path coefficients were first analyzed to capture both the strength and direction of relationships between variables, offering a direct view of how one construct influences another. To determine whether these relationships were statistically meaningful, a significance test was carried out using bootstrapping with 5000 samples, where t-statistics and p-values served as the basis for inference; relationships with p-values below 0.05 were treated as significant.

The model's explanatory power was then assessed through the R-Squared (R^2) value, which indicates how well the independent variables account for variation in the dependent variable, with higher values reflecting stronger explanatory capacity. Model fit was then evaluated using SRMR and NFI. The Standardized Root Mean Square Residual (SRMR) captures the average discrepancy between the observed data and the model's predictions, with values ranging from 0 to 1, where smaller values signal closer alignment. An SRMR value of ≤ 0.08 was taken to reflect a good fit, while values below 0.05 indicated an even tighter fit between the model and the data [29],[30],[44]. Complementing this, the Normed Fit Index (NFI) compared the proposed model against a baseline model without adjusting for complexity; values closer to 1 suggested a better fit, and scores of 0.90 or higher were considered indicative of a well-fitting model [30], [44].

Hypothesis Testing

After completing the structural model analysis, attention shifts to testing the proposed research hypotheses. At this stage, the focus narrows to examining whether the relationships outlined in the conceptual framework are supported

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by empirical evidence. Each hypothesis, including those addressing the influence of Condition-Based Maintenance (CBM) on heavy equipment performance, is evaluated through significance testing of the corresponding path coefficients. These coefficients do more than indicate direction; they quantify how strongly one variable affects another within the model.

The decision-making process relies on p-values derived from the earlier bootstrapping procedure. A p-value below 0.05 is treated as clear statistical support, suggesting that the observed relationship is unlikely to have occurred by chance alone. When this threshold is met, the hypothesis is accepted, reinforcing the proposed linkage between variables. On the other hand, values above this cutoff signal insufficient evidence, prompting the rejection of the hypothesis. Through this step, the analysis moves from model estimation to interpretation, translating numerical results into meaningful conclusions about the relationships under study.

Moderation Analysis

This research also tests the moderating effect (Operational Environmental Conditions and HR Competence) on the relationship between variables. Some of the steps taken are the Moderation Test, namely to test whether the moderating variables (Operational Environmental Conditions and Human Resource Competence) strengthen or weaken the relationship between CBM and heavy equipment performance. Therefore this study test the complex conceptual model (including moderating effect) using SEM-PLS with rules based on Hair theory [30]. Partial Least Squares Structural Equation Modeling (PLS-SEM) was used to moderate analysis whether operational environmental condition and HR competence moderates affect the relationship of Condition-Based Maintenance (CBM) and heavy equipment performance. Before assessing the moderating effects, all latent constructs—including CBM, HR competence, environmental conditions, and equipment performance—were carefully checked to ensure measurement model adequacy.

The moderator's effects were tested via two-stage approach utilizing PLS-SEM experimentation. The first step was to estimate latent variable scores for all constructs in the model: CBM Planning (X1), CBM Monitoring and Diagnosis (X2), CBM Decision Support (X3), Operational Environmental Conditions (Z1), Human Resource Competency (Z2) and Heavy Equipment Performance (Y). In the second step, interaction term was created by multiplying the latent variable scores for each of the CBM dimensions to its associated moderator. Figure 4 presents an overview of the six interaction constructs (X1×Z1, X2×Z1, X3×Z1, X1×Z2, X2×Z2 and X3×Z2) in generating Hypotheses H4–H9. Next, these interaction constructs were included as additional predictors of Heavy Equipment Performance in the structural model. Bootstrapping procedures were used to evaluate the significance of the moderating effects. To assess whether each interaction term significantly changed the relationship between the corresponding dimension of CBM and Heavy Equipment Performance, we looked at path coefficients, t-values, and p-values. Effect size (f^2) values were also examined to assess the magnitude of moderation effects by comparing the explanatory power of the model with and without the inclusion of interaction terms.

Research Steps

The study was conducted using multiple methodological phases (Figure 2). In the first stage, the research problem and an analytical framework for problems of heavy-equipment maintenance performance at coal mining operations were identified. The second phase consists of developing the research model, hypotheses about the relationships between CBM implementation and both operational environmental conditions and human resource competency, as well as heavy equipment performance. In the next step, measurement items were developed based on literature and tested in an expert review followed by a pilot test. After the instrument was developed, data were collected from

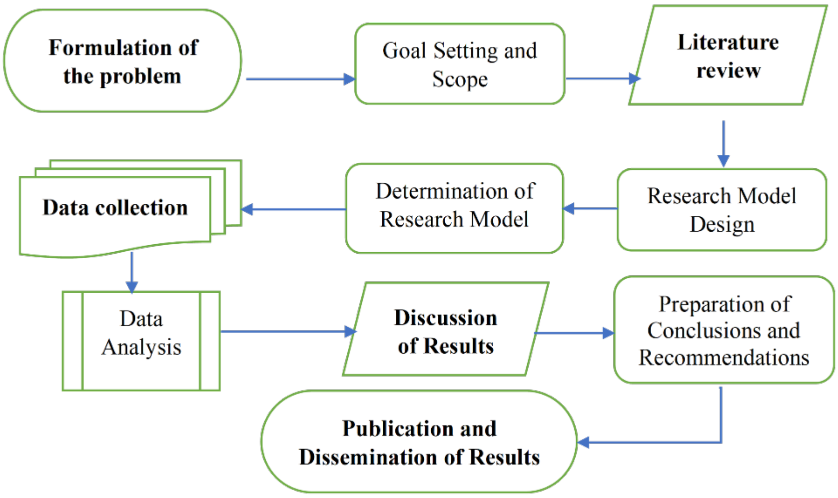

Figure 2. Research Steps

operational and maintenance personnel of coal mining companies with implemented CBM practices. Finally, data was analysed through PLS-SEM. Assessment of the measurement model, structural relationships evaluation, and testing moderation through interaction terms were part of the analysis. The final stage involved interpreting the empirical findings in relation to the proposed hypotheses and deriving implications for maintenance management in coal mining operations.

RESULTS AND DISCUSSION

Measurement Model Analysis (Outer Model)

An outer model was generated to provide an overview of the relationship between the latent variables (constructs) with each indicator. This model helps to illustrate the effect of the variables towards the indicators as well as the validity from the variables of the research. Based on the results of data processing using PLS from Figure 3, it shows that all indicators have an outer loading factor of > 0.7 (have outer loading value in the range of 0.907 - 0.949) so it is concluded that all indicators have met the requirements for Convergent Validity and are valid indicators for use in measuring the six research variables. The SEM-PLS model in this study was estimated using the Alternating Least Squares (ALS) algorithm in Smart-PLS 4.0. The ALS algorithm works iteratively by updating the latent variable scores through an alternating estimation process between the outer model (measurement model) and the inner model (structural model) until convergence is achieved.

Fornell-Larcker Criterion: The AVE root value (diagonal) must be greater than the correlation between constructs. From Table 2, all AVE diagonals are higher than the correlation between constructs, meaning that all constructs have good discriminant validity [30].

Structural Model Evaluation (Inner Model)

According to [30,44], the evaluation of structural model (inner model) in PLS analysis consists of a significance test and an R^2 endogenous variable calculation. The model of statistical significance test was conducted using bootstrapping (resampling) method. At the confidence interval of 95%, the exogenous variables significantly influenced the endogenous variables when the value p-value is <0.05. The value of R^2 was used to give a score in measuring the influences of dependent latent variable to the independent latent variable.

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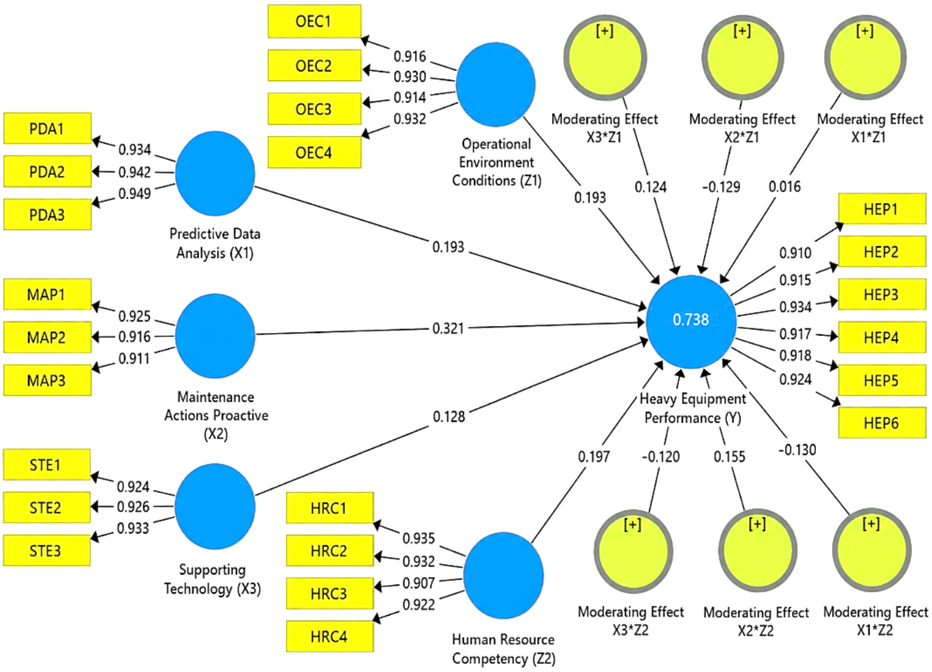

Figure 3. ALS Algorithm Result

Table 2. Fornell-Larcker Criterion

	HEP (Y)	HRC (Z2)	MAP (X2)	X1*Z1	X1*Z2	X2*Z1	X2*Z2	X3*Z1	X3*Z2	OEC (Z1)	PDA (X1)	STE (X3)
Heavy Equipment Performance (Y)	0.920											
Human Resource Competency (Z2)	0.669	0.924										
Maintenance Actions Proactive (X2)	0.762	0.565	0.917									
Moderating Effect X1*Z1	-0.109	0.005	-0.071	0.880								
Moderating Effect X1*Z2	-0.111	0.007	-0.041	0.738	0.873							
Moderating Effect X2*Z1	-0.070	0.037	-0.006	0.733	0.507	0.848						
Moderating Effect X2*Z2	-0.041	0.079	-0.003	0.587	0.726	0.699	0.849					
Moderating Effect X3*Z1	-0.071	0.037	-0.104	0.774	0.562	0.743	0.574	0.873				
Moderating Effect X3*Z2	-0.068	0.077	-0.051	0.626	0.746	0.568	0.771	0.751	0.866			
Operational Environment Conditions (Z1)	0.675	0.660	0.599	0.012	0.007	0.028	0.036	0.053	0.024	0.923		
Predictive Data Analysis (X1)	0.677	0.514	0.667	-0.093	-0.037	-0.075	-0.053	-0.060	-0.001	0.454	0.941	
Supporting Technology (X3)	0.665	0.485	0.688	-0.061	0.007	-0.113	-0.059	-0.076	-0.006	0.517	0.653	0.928

Table 3. R-Square

	R Square	**R Square Adjusted**
Heavy Equipment Performance (Y)	0.738	0.723

Tabel 4. Construct Reliability and Validity

Construct Reliability and Validity	**Cronbach's Alpha**	**ρ_A**	**Composite Reliability**	**AVE**
Heavy Equipment Performance (Y)	0.964	0.964	0.970	0.846
Human Resource Competency (Z2)	0.943	0.944	0.959	0.854
Maintenance Actions Proactive (X2)	0.906	0.906	0.941	0.841
Moderating Effect X1*Z1	0.974	1.000	0.976	0.774
Moderating Effect X1*Z2	0.973	1.000	0.975	0.762
Moderating Effect X2*Z1	0.970	1.000	0.968	0.719
Moderating Effect X2*Z2	0.968	1.000	0.969	0.720
Moderating Effect X3*Z1	0.973	1.000	0.975	0.762
Moderating Effect X3*Z2	0.973	1.000	0.973	0.749
Operational Environment Conditions (Z1)	0.942	0.943	0.958	0.852
Predictive Data Analysis (X1)	0.936	0.938	0.959	0.886
Supporting Technology (X3)	0.919	0.921	0.949	0.860

The R^2 value for the Heavy Equipment Performance (Y) construct based on Table 3 concludes that the R-Square value for the endogenous variable Heavy Equipment Performance is 0.738, which indicates that the variability of Predictive Data Analysis, Maintenance Actions Proactive, Supporting Technology, Operational Environment Conditions and Human Resource Competency has an impact of 0.738 or equivalent to 73.8% on Heavy Equipment Performance. Meanwhile, the adjusted R value of 0.723 or 72.3% indicates that after considering the number of predictors, the model's explanatory power remains in the strong category. The calculation results show that all constructs have CR, CA and AVE values above 0.7 so it can be concluded that all constructs have good reliability (See Table 4).

The F-Square (f^2) results show that most predictor variables have weak effect sizes on Heavy Equipment Performance, including Predictive Data Analysis (0.065), Maintenance Actions Proactive (0.138), Supporting Technology (0.027), Operational Environment Conditions (0.066), and Human Resource Competency (0.072) (see Table 5). Although several relationships are statistically significant, these weak f^2 values indicate that statistical significance does not necessarily imply strong practical impact. Practically, this suggests that individual CBM factors contribute only marginally when implemented in isolation. Therefore, in the mining industry context, CBM should be prioritized as an integrated system, where performance improvements are achieved through the combined and synergistic implementation of multiple CBM dimensions rather than isolated initiatives. Table 6 presents the model fit results from the SEM-PLS analysis. The Standardized Root Mean Square Residual (SRMR) value is 0.033, indicating an excellent fit between the model and the observed data. In addition, the Normed Fit Index (NFI) reaches 0.918, which reflects a good overall model fit. Together, these values suggest that the proposed model aligns well with the empirical data and provides a satisfactory representation of the underlying relationships.

Hypothesis Testing (Path Coefficient and Bootstrapping)

In the model evaluation, the significance is seen to determine the influence between variables through the Bootstrapping procedure. Hypothesis testing is done by looking at the t-statistics value and the P Values value. The

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Table 5. F-Square

f Square	**Heavy Equipment Performance (Y)**
Heavy Equipment Performance (Y)	
Human Resource Competency (Z2)	0.072
Maintenance Actions Proactive (X2)	0.138
Moderating Effect X1*Z1	0.000
Moderating Effect X1*Z2	0.015
Moderating Effect X2*Z1	0.015
Moderating Effect X2*Z2	0.020
Moderating Effect X3*Z1	0.012
Moderating Effect X3*Z2	0.011
Operational Environment Conditions (Z1)	0.066
Predictive Data Analysis (X1)	0.065
Supporting Technology (X3)	0.027

Table 6. Model Fit Test

Fit Summary	Saturated Model	Estimated Model
SRMR	0.033	0.033
d_ULS	0.308	0.307
d_G	0.346	0.345
Chi-Square	436.996	436.131
NFI	0.918	0.918

hypothesis in this study can be declared accepted if the P value result is equal to or below ($p \leq 0.05$), and the T-statistic is 1.96 at significance level = 0.05 [30], [44].

Based on Figure 4 and Table 7, each hypothesized relationship was examined through simulation using a PLS-SEM approach. To address potential issues related to non-normal data distribution, the analysis employed a bootstrapping

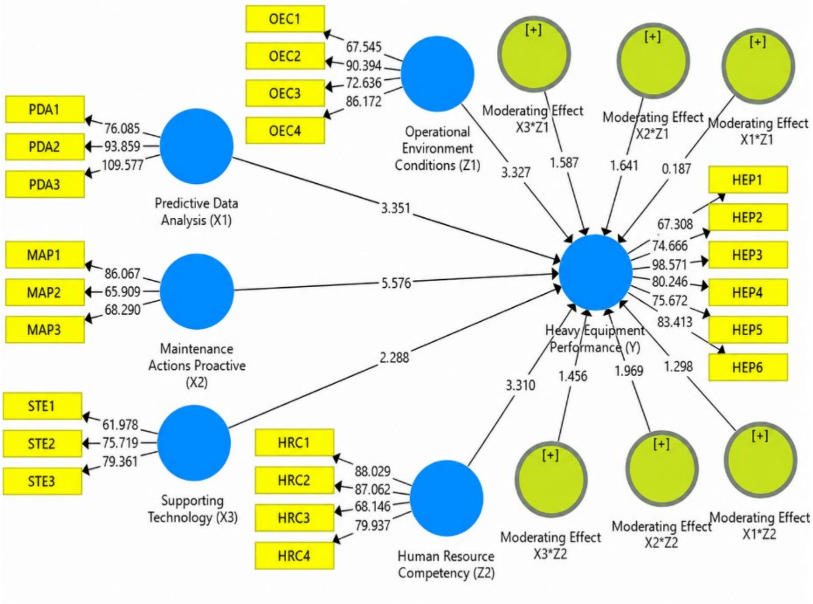

Figure 4. Bootstrapping Result

Table 7. Hypothesis Testing

Mean, STDEV, T-Values, P-Values	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P- Values
Human Resource Competency (Z2) -> Heavy Equipment Performance (Y)	0.197	0.196	0.060	3.310	0.001
Maintenance Actions Proactive (X2) -> Heavy Equipment Performance (Y)	0.321	0.317	0.057	5.576	0.000
Moderating Effect X1*Z1 -> Heavy Equipment Performance (Y)	0.016	-0.007	0.085	0.187	0.852
Moderating Effect X1*Z2 -> Heavy Equipment Performance (Y)	-0.130	-0.104	0.100	1.298	0.195
Moderating Effect X2*Z1 -> Heavy Equipment Performance (Y)	-0.129	-0.061	0.079	1.641	0.102
Moderating Effect X2*Z2 -> Heavy Equipment Performance (Y)	0.155	0.080	0.079	1.969	0.050
Moderating Effect X3*Z1 -> Heavy Equipment Performance (Y)	0.124	0.078	0.078	1.587	0.113
Moderating Effect X3*Z2 -> Heavy Equipment Performance (Y)	-0.120	-0.071	0.083	1.456	0.146
Operational Environment Conditions (Z1) -> Heavy Equipment Performance (Y)	0.193	0.198	0.058	3.327	0.001
Predictive Data Analysis (X1) -> Heavy Equipment Performance (Y)	0.193	0.186	0.058	3.351	0.001
Supporting Technology (X3) -> Heavy Equipment Performance (Y)	0.128	0.127	0.056	2.288	0.023

procedure, which allows for more stable and reliable estimation of parameter significance without relying on strict normality assumptions. Through repeated resampling, this method provides robust estimates of standard errors, t-statistics, and p-values for each path. The results derived from the bootstrapping process are presented in Figure 4 and further detailed in the following discussion, offering a clearer view of the strength and significance of the proposed relationships within the model.

1. **H1:** Predictive Data Analysis (X1) on Heavy Equipment Performance (Y): The path coefficient was 0.193, with a P-Value of 0.001 and a positive T-Statistic of 3.351. It can thus be concluded that Predictive Data Analysis (X1) significantly influences Heavy Equipment Performance (Y). H1 is accepted, and H0 is rejected.
2. **H2:** Maintenance Actions Proactive (X2) on Heavy Equipment Performance (Y): The path coefficient was 0.321, with a P-Value of 0.000 and a positive T-Statistic of 5.576. It can thus be concluded that Maintenance Actions Proactive (X2) significantly influences Heavy Equipment Performance (Y). H1 is accepted, and H0 is rejected.
3. **H3:** Supporting Technology (X3) on Heavy Equipment Performance (Y): The path coefficient was 0.128, with a P-Value of 0.023 and a positive T-Statistic of 2.288. It can thus be concluded that Supporting Technology (X3) significantly influences Heavy Equipment Performance (Y). H1 is accepted, and H0 is rejected.
4. **H4:** Operational Environment Conditions (Z1) moderating Predictive Data Analysis (X1) on Heavy Equipment Performance (Y): The path coefficient was 0.016, with a P-Value of 0.852 and a T-Statistic of 0.187. Thus, Operational Environment Conditions (Z1) does not significantly moderate the relationship between Predictive Data Analysis (X1) and Heavy Equipment Performance (Y). H1 is rejected, and H0 is accepted.

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5. **H5:** Operational Environment Conditions (Z1) moderating Maintenance Actions Proactive (X2) on Heavy Equipment Performance (Y): The path coefficient was -0.129, with a P-Value of 0.102 and a T-Statistic of 1.641. Thus, Operational Environment Conditions (Z1) does not significantly moderate the relationship between Maintenance Actions Proactive (X2) and Heavy Equipment Performance (Y). H1 is rejected, and H0 is accepted.
6. **H6:** Operational Environment Conditions (Z1) moderating Supporting Technology (X3) on Heavy Equipment Performance (Y): The path coefficient was 0.124, with a P-Value of 0.113 and a T-Statistic of 1.587. Thus, Operational Environment Conditions (Z1) does not significantly moderate the relationship between Supporting Technology (X3) and Heavy Equipment Performance (Y). H1 is rejected, and H0 is accepted.
7. **H7:** Human Resource Competency (Z2) moderating Supporting Technology (X3) on Heavy Equipment Performance (Y): The path coefficient was -0.120, with a P-Value of 0.146 and a T-Statistic of 1.456. Thus, Human Resource Competency (Z2) does not significantly moderate the relationship between Supporting Technology (X3) and Heavy Equipment Performance (Y). H1 is rejected, and H0 is accepted.
8. **H8:** Human Resource Competency (Z2) moderating Maintenance Actions Proactive (X2) on Heavy Equipment Performance (Y): The path coefficient was 0.155, with a P-Value of 0.050 and a T-Statistic of 1.969. Thus, Human Resource Competency (Z2) significantly moderates the relationship between Maintenance Actions Proactive (X2) and Heavy Equipment Performance (Y). H1 is accepted, and H0 is rejected.
9. **H9:** Human Resource Competency (Z2) moderating Predictive Data Analysis (X1) on Heavy Equipment Performance (Y): The path coefficient was -0.130, with a P-Value of 0.195 and a T-Statistic of 1.298. Thus, Human Resource Competency (Z2) does not significantly moderate the relationship between Predictive Data Analysis (X1) and Heavy Equipment Performance (Y). H1 is rejected, and H0 is accepted.
10. **H10:** Operational Environment Conditions (Z1) on Heavy Equipment Performance (Y): The path coefficient was 0.193, with a P-Value of 0.001 and a positive T-Statistic of 3.327. It can thus be concluded that Operational Environment Conditions (Z1) significantly influences Heavy Equipment Performance (Y). H1 is accepted, and H0 is rejected.
11. **H11:** Human Resource Competency (Z2) on Heavy Equipment Performance (Y): The path coefficient was 0.197, with a P-Value of 0.001 and a positive T-Statistic of 3.310. This means that Human Resource Competency (Z2) has a significant effect on Heavy Equipment Performance (Y). We accept H1 while we reject H0.

Discussion

This research intends to investigate the impact of CBM implementation from three major variables: Predictive Data Analysis (PDA), Maintenance Actions Proactive (MAP), and Supporting Technology (STE), towards Heavy Equipment Performance (HEP) with Operational Environment Conditions (OEC) and Human Resource Competency (HRC) as moderators. This is the analysis/discussion of your findings from previous calculations:

1. *Influence of Predictive Data Analysis on Heavy Equipment Efficiency:*

The findings can confirm the positive and significant effect of PDA on HEP. Predictive Data Analysis helps Heavy Equipment to perform better — Understanding the impact of failure detection and predictions prior to breaks for operational efficiency Essentially, it means that maintenance personnel can draw up an intervention schedule for equipment based on its condition rather than using fixed maintenance intervals. This minimizes the risk of unplanned breakdowns and ensures that production operations do not face equipment downtime.

Th The nature of this result confirms the contributions reported by previous studies on the predictive accuracy of analytics used in condition prediction, fault detection and maintenance decision-making [32], [33], [45], [46]. Earlier research primarily emphasized improvements in prediction accuracy and diagnostic capability. The present result supports those observations by showing that the benefits of predictive analysis are also reflected in operational performance indicators within a mining environment. The result further suggests that the effectiveness of predictive analysis depends on the availability of reliable condition data and the ability of personnel to translate analytical outputs into maintenance actions. Under heavy-equipment operating conditions, predictive information alone may be insufficient unless it is incorporated into day-to-day maintenance planning and execution processes.

2. *Influence of Preventive Adjustments Proactive (PAP) on Heavy Machines Performance (HMP)*

The findings indicate that Maintenance Actions Proactive has the highest path coefficient magnitude for CBM variables, leading to a relatively stronger relationship with Heavy Equipment Performance than the other predictors. However, the effect size associated with it is still small ($f^2 = 0.138$), which indicates that even though MAP is the variable that contributes to performance improvement in relative terms more than the others, its contribution in absolute terms is still modest. This nuanced finding confirms prior studies [34] [35] [47], [48] emphasizes preemptive maintenance execution is the fulcrum to materialize CBM performance benefits and extends current research evidencing these performance advantages are incremental (rather than abrupt) and are dispersed over multiple adjacent capabilities. Thus, MAP is to be treated as the primary (but not only) driver for when uncertainty and generality are offset by targeted analysis of predictive data and application of distal technologies in mining.

3. *Effect of Supporting Technology (STE) to Heavy Equipment Performance (HEP)*

In brief, the results are: General Support Technology significant positive effect Heavy Equipment Performance, that is to say General Support technology as it enables CBM. This could be partly in line with early studies emphasizing sensors wireless networks and unusual monitoring systems for maintenance optimization, but in contrast to the literature it is demonstrated this through technology improvement will not lead performance. Rather its value emerges when fully integrated with predictive analytics and proactive maintenance activities. This supports the perspective that supporting technology is not a stand-alone determinant of CBM performance in mining operations, but rather a foundational enabler [34, 35].

4. *Moderation by OEC on the PDA–HEP Relationship*

In the preceding table, OEC does not moderate significantly on the relationship between Predictive Data Analysis and Heavy Equipment Performance. This might imply that the capability of predictive analytics is relatively consistent for the operational environment as encapsulated in the selected mining sites sampled, which tend to adhere to well-defined environmental and operational conditions. Also, the OEC measure may reflect general environmental harshness versus extreme or stress-buffering environments, which could render it less sensitive to interaction effects. In theory, this finding suggests that the performance of PDA is more affected by its internal chain quality and analytical capability than changes in external conditions (in line with previous reports [33], [34], [46], [47].

5. *Moderated Mediation of the MAP–HEP Relationship by Operational Environment Conditions (OEC)*

The absence of a large moderating effect indicates that proactive maintenance behaviors influence machinery performance irrespective of the environment. In practice, most mining companies use the same standard maintenance criteria and factors of safety to counteract environmental uncertainty, thus may less distinguish the effect of OEC. Additionally, reduced variation in environmental conditions among sampled sites may have limited the potential for moderation effects. This supports the theoretical argument that MAP is a hard 21 internal capacity, whose performance is less dependent on the outside operational environment [46], [47].

6. Moderation of the Relationship Between STE and HEP by OEC

The non-significant moderation suggests that the performance gain of user-supporting technology can be kept stable since its deployment regardless of environmental conditions. Today's monitoring and and maintenance technologies are often built to endure the tough mining conditions, which might cancel out the anticipated interaction with OEC. From a measurement standpoint, the OEC indicators might not adequately distinguish between technology supporting and technology opposing settings. This result is an extension of previous studies [47], [48] by indicating that OEC affect the adoption decision in technology but not necessarily its impact on performance after implementation.

7. Moderating Effect of Human Resource Competence (HRC) on the STE–HEP Relationship

The inconclusive moderating effect points out that HR competency is not enough to strengthen the performance implication of enabling technology. This suggests that the potential of technology enabled CBM benefits is largely due to system capability and integration maturity rather than operator skill. Where technology uptake is uneven or only partially implemented, a capable workforce may have little influence on performance improvement. This finding extends previous research [34], [41] and suggests that HRC is a contingency factor when technological readiness is less than perfect.

8. Moderating Effect of HRC on MAP-HEP Relationship

According to the results, HRH moderates the degree and strength of influence from MAP towards HEP (P-Value: 0.050, T-Statistic: 1.969). Perform the best trained technicians that are carrying out proactive maintenance activities in order to maximize heavy machine performance. This yield consistent with findings in [48], [49]. The high level of moderation effect of Human Resource Competency in Table 5 shows that higher level of competency would boost the positive contribution from proactive maintenance actions to heavy equipment performance. Well trained technicians can improve the effectiveness of MAP through increasing diagnostic capabilities, ranking interventions by degradation level or severity, and timing maintenance perfectly. Nevertheless, although statistically significant, the moderation effect size is negligible ($f^2 = 0.020$): small practical implications are suggested. This implies that HRC plays a role more like a fine-tuning agent rather than the primary function. This means that from a managerial viewpoint, training and competence development should be worked alongside standardized proactive maintenance systems, since investing in human competence only is unlikely to yield significant performance improvements if MAP processes are not robust.

9. Moderating Effect of Human Resource Competence (HRC) on the PDA–HEP Relationship

The lack of a strong moderating effect could suggest that in the presence of simplistic models, low quality data or simple systems alone personnel are not enough to enhance the impact of predictive data analysis. This suggests that the impact of PDA is less driven by individual expertise than it is by analytic infrastructure and methodological maturity. This may provide a more nuanced understanding of some of the known results related to previous investigations [40], [49], in that there seems to be law does seem to distinguish between normative interpretations and capability and skill gap, given that it is has less insight about defining advanced predictive analytics skills.

10. Effect of Operational Environment Conditions (OEC) on Heavy Equipment Performance (HEP)

OEC's direct effect is indeed tangible in the realization that environmental extremity remains an important prerequisite for superior performance on heavy equipment use in mining. This finding corroborates earlier studies [39], [40], but extends them by showing that even when OEC activities are incorporated into CBM, they present a direct performance barrier. This helps our claim that the environmental conditions work better as a boundary condition in an environmental contingent way, instead of a moderator in CBM relationships.

11. The Influence of Human Resource Competency (HRC) of Heavy Equipment Performance (HEP)

The pronounced effect of HRC on the performance of equipment indicates that human capital is a central mediating mechanism in operation within CBM systems. The fact that this finding, on the contrary, is somewhat in line with socio-technical systems views arguing for human sense-making and acting as still needed alongside technical development. This finding not only confirms previous work [42], [50], [51] but also extends it by showing that poor performance in CBM systems does not so much arise from technology levels, but from operator unawareness and neglect(negligence).

In short, this work is an archetypical example of the implementations of CBM into mining. The key to success in preventive maintenance is taking action based on quality predictive data. However, technology assistance and manpower are not presently enough to fully exploit the CBM potential as environmental operating conditions are relevant but hard to totally control.

Research Limitations

This study makes a solid contribution to the development of complex Condition-Based Maintenance (CBM) strategies and the understanding of heavy equipment performance in the mining sector. Still, several limitations need to be acknowledged. The research adopts a cross-sectional design, which captures conditions at a single point in time, whereas CBM is inherently a long-term process that unfolds through continuous monitoring and gradual refinement. This gap means the study cannot fully reflect how CBM evolves or performs over extended operational periods. In addition, the data rely on respondents' perceptions collected through questionnaires rather than objective performance indicators such as mean time between failure, mean time to repair, or equipment availability rates. While practical, this approach opens the door to cognitive bias, including overly optimistic assessments that may not align with actual equipment performance.

The model also positions operational conditions and human resource competence as mediating variables, offering a structured way to examine their influence but potentially simplifying complex interactions found in real mining environments. The non-significant moderation results in H4–H7 and H9 further suggest that the relationships between CBM factors and heavy equipment performance remain relatively stable across variations in operational environment and workforce capability within the sampled sites. This consistency likely reflects the high similarity of environmental conditions and the standardized maintenance practices used to maintain IOA across locations, which reduces variation and limits the emergence of moderation effects. A similar pattern appears in the weak moderation involving predictive data analysis and supporting technology, pointing to system capability and process maturity as stronger drivers than organizational differences. From a methodological angle, the linear interaction approach applied here may not fully capture more complex patterns, such as threshold or non-linear effects where environmental or competency factors only influence performance beyond certain critical levels. Alternative approaches, including multi-group analysis and non-linear modeling, could provide a more sensitive lens for detecting these context-driven dynamics.

Finally, the scope of the study is confined to a single industrial setting—coal mining contractors—with specific organizational structures and technological conditions. As a result, the findings should be interpreted with caution when considering their application to other sectors, such as oil and gas, manufacturing, or construction, where operational realities and maintenance systems may differ in meaningful ways..

CONCLUSION

The study centers on one clear pattern. Maintenance execution carries the weight. Among the three CBM elements, proactive maintenance actions stand out as the most decisive contributor to heavy equipment performance. Not because data and technology lack value, but because their impact depends on what happens in the field. When maintenance is timely, planned, and actually carried out, performance improves in a visible way. Remove that discipline, and the rest loses force. Predictive analysis and supporting tools still matter. They shape decisions, guide

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priorities, and reduce guesswork, yet their influence remains indirect. They act as enablers, not drivers. Another layer sits in the background. Operating conditions and workforce capability both connect to performance outcomes, but they rarely change the strength of how CBM elements translate into results. This points to something practical: outcomes rely less on context variation and more on consistency in execution.

From a management angle, the implications tighten further. Focus should stay on getting maintenance actions right—planned, timed, and completed without drift. That is where most of the value concentrates. Analytical tools should be treated as guidance systems, useful only when their outputs lead to action. More data alone does not shift performance. What matters is whether insight turns into decisions and those decisions turn into work on the equipment. At the same time, skill development should not be broad and unfocused. It should sharpen the technician's ability to interpret, decide, and execute maintenance tasks with precision, since this is where competency shows its real effect. Environmental conditions cannot be ignored either. They place continuous pressure on equipment, shaping wear, reliability, and stability in daily operations. Improving road quality, controlling dust, managing water, and adjusting schedules during harsh conditions all help reduce that pressure. In the end, strong results come from alignment—clear decisions, disciplined execution, capable people, and operating conditions that do not quietly erode performance.

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CONFLICT OF INTEREST

The authors declare that there is no conflict of interest regarding the publication of this article.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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