INTERNATIONAL JOURNAL OF MULTIDISCIPLINARY: APPLIED BUSINESS AND EDUCATION RESEARCH
2025, Vol. 6, No. 9, 4810 – 4829
http://dx.doi.org/10.11594/ijmaber.06.09.41

Research Article

Fuel Consumption Efficiency in Construction Equipment Operations: A Mixed Methods Analysis of Determinants and Practices

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Article history:
Submission 03 August 2025
Revised 31 August 2025
Accepted 23 September 2025

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ABSTRACT

This study examines the key factors affecting fuel consumption efficiency in construction equipment operations. Using a mixed methods approach, it combines quantitative regression analysis with qualitative interviews of equipment operators. A survey was conducted to gather data on operator behavior, equipment maintenance, equipment condition, worksite environment, and operator experience and training. Regression results showed that among these factors, only operator experience and training significantly predicted fuel efficiency, with $R^2 = .31$. Other variables, such as operator behavior, maintenance practices, equipment condition, and worksite environment, were not statistically significant predictors. Qualitative interviews supported these findings. Operators emphasized the importance of situational awareness, experience, and task-specific adjustments in saving fuel. Common strategies included managing engine RPM according to workload, shutting down equipment during idle periods, and using neutral gear on downhill slopes when safe. These practices rely more on operator judgment than on technical specifications. While maintenance, equipment condition, and environmental factors were frequently mentioned, their influence appears indirect or context-dependent. This suggests that technical improvements alone are insufficient without skilled operator input. The study concludes that operator training and experience, play a central role in fuel efficiency. It recommends that construction firms invest in targeted training and behavior-based monitoring to promote sustainable and efficient equipment use.

***Keywords**: Construction equipment operations, Fuel consumption efficiency, Human factors, Operator experience, Operator training, Regression analysis, Situational awareness*

How to cite:
Gabriel, J. A. M. & Narsico, P. G. (2025). Fuel Consumption Efficiency in Construction Equipment Operations: A Mixed Methods Analysis of Determinants and Practices. *International Journal of Multidisciplinary: Applied Business and Education Research. 6*(9), 4810 – 4829. doi: 10.11594/ijmaber.06.09.41

Background

Fuel consumption in construction equipment operations is a critical concern in the construction industry, not only due to its substantial contribution to operational costs but also because of its environmental implications. Earthwork activities, for example, consume large quantities of fossil fuel and produce substantial air pollution, making them a major source of nonroad emissions (Hong & Lü, 2022). Despite technological advancements in machinery and fuel systems, inefficiencies in fuel usage remain prevalent across many construction sites (Akhavian & Behzadan, 2013). These inefficiencies are often linked to a combination of behavioral practices, equipment maintenance routines, machine conditions, and environmental factors (Rasdorf, Frey, Lewis, & Kim, 2010). Operators may lack formal training in fuel-saving techniques, equipment may not be maintained regularly, and site conditions may pose challenges to efficient operation (Lewis, Leming, Rasdorf, Frey, & Kim, 2011). Moreover, idle time management has emerged as a key factor in reducing fuel consumption and emissions, yet it is often overlooked in daily operations (Frey, Bammi, & Unal, 2009). As the industry continues to seek ways to improve productivity and sustainability, understanding the multifaceted influences on fuel consumption becomes increasingly important (Alzahrani & Emsley, 2013).

Despite increasing attention to fuel efficiency in construction, much of the recent literature continues to prioritize technological innovations, fuel types, and emissions modeling, while giving limited focus to behavioral and operational dimensions of fuel usage (Golbasi & Kina, 2021; National Academies of Sciences, Engineering, and Medicine, 2020). Although some studies have explored idle time management and emissions tracking, few have systematically examined how operator behavior, maintenance practices, equipment condition, worksite environment, and operator experience collectively influence fuel consumption efficiency (Zhang et al., 2023; Jin et al., 2019). Moreover, the integration of these factors into a unified framework remains underdeveloped, leaving a gap in understanding how they interact in real-world construction settings. This lack of comprehensive analysis limits the ability of construction managers and policymakers to implement targeted interventions that address both technical and human factors. Therefore, this study aims to fill that gap by using a survey-based approach to identify and analyze the key determinants of fuel consumption efficiency, offering insights that can inform training programs, operational strategies, and sustainable construction practices (Scora et al., 2021).

Fuel consumption in construction equipment operations constitutes a substantial portion of both operational costs and environmental impact within the construction industry. Despite technological advancements in machinery and fuel systems, inefficiencies in fuel usage continue to persist, often stemming from a complex interplay of behavioral, mechanical, and environmental factors. On many construction sites, operators may lack formal training in fuel-efficient practices, equipment may not be maintained according to optimal standards, and site conditions may hinder efficient operations. These challenges underscore the importance of systematically investigating the determinants of fuel consumption efficiency in construction equipment operations. A deeper understanding of these factors is crucial for designing targeted interventions that can reduce fuel costs, enhance productivity, and support sustainable construction practices. Accordingly, this study seeks to answer the following research questions: (1) How do respondents rate the influence of each operational factor on fuel consumption efficiency? (2) To what extent does operator behavior influence fuel consumption efficiency in construction equipment operations? (3) How do equipment maintenance practices affect the fuel efficiency of construction machinery? (4) What is the relationship between equipment condition and fuel consumption efficiency? (5) How do worksite environmental factors contribute to variations in fuel usage? (6) What role do operator experience and training play in promoting fuel-efficient practices? (7) What are the practical implications of the identified determinants for improving fuel consumption efficiency in construction equipment operations? To address these questions, the following null hypotheses are proposed: H_{01}: Operator behavior has no significant influence on fuel consumption efficiency in construction equipment operations. H_{02}: Equipment maintenance practices do not significantly affect the fuel efficiency of construction machinery. H_{03}: Equipment condition has no significant relationship with fuel consumption efficiency. H_{04}: Worksite environmental factors do not significantly contribute to variations in fuel usage. H_{05}: Operator experience and training have no significant effect on fuel-efficient practices.

Methods

Research Design and Respondents

This study employed a mixed methods approach, combining quantitative and qualitative components to comprehensively examine fuel consumption efficiency in construction equipment operations. The quantitative aspect utilized a descriptive-correlational research design to identify determinants of fuel efficiency by analyzing patterns and relationships among operational practices, equipment characteristics, and fuel usage behaviors. Complementing this, the qualitative component involved interviews with all the 30 respondents to explore insights and emerging themes on how fuel efficiency can be achieved in practice.

This approach was chosen to enable a systematic collection and integration of numerical data with contextual perspectives, enriching the overall analysis. Participants included individuals directly involved in construction equipment operations—such as equipment operators, site supervisors, and maintenance personnel—who possessed extensive field experience. A purposive sampling technique was employed to ensure that respondents had relevant expertise and familiarity with fuel consumption practices. The final sample size was determined based on accessibility, relevance, and the need to ensure statistical reliability, while also accounting for diversity in equipment types and operational contexts. A total of 30 operators were screened for competency to meet the inclusion criteria of the study.

Instruments

Data were collected using a structured questionnaire developed by the researchers, drawing from existing literature and refined through expert consultation to ensure content validity. The instrument was organized into several sections, including operator behavior, equipment maintenance practices, equipment condition, worksite environmental, and operator experience and training. Prior to full deployment, the questionnaire underwent pilot testing to evaluate clarity and reliability. Based on feedback, necessary revisions were made. The instrument demonstrated strong internal consistency, with a Cronbach's alpha reliability coefficient of 0.828.

The questionnaire has six parts. The first part examines operator behaviors that influence fuel efficiency. Turning off engines during idle times (Akhavian & Behzadan, 2013), avoiding unnecessary acceleration (Joumard, 1995), following proper procedures (Zhang & Hill, 2021), and planning routes to reduce backtracking (Zhang & Zhang, 2020) are all practices linked to reduced fuel consumption. The second part focuses on maintenance-related practices that affect fuel efficiency. Regular scheduled maintenance ensures equipment runs optimally, reducing fuel waste (Kumar et al., 2021). Preventive maintenance before and after use helps avoid breakdowns and inefficiencies (Al-Hussein et al., 2020). Inspecting and cleaning fuel system components like filters and injectors improves combustion and fuel economy (Lohse-Busch et al., 2020). Prompt reporting of equipment issues allows timely repairs, preventing fuel inefficiencies due to malfunctioning systems (Zhou et al., 2022).

The third part addresses how the condition of construction equipment affects fuel efficiency. Well-maintained equipment tends to consume less fuel due to optimal performance (Zhou et. al., 2022). Older or poorly maintained machines often show reduced fuel economy, as noted by Kumar, Singh, and Sharma (2021). Efficient engine and fuel system performance is also critical, as it ensures proper combustion and minimizes fuel waste (Lohse-Busch et al., 2020). Additionally, Al-Hussein, Niaz, and Yu (2020) found that operators experience fewer fuel-related issues when using equipment that is consistently kept in good condition. The fourth part explores how environmental conditions at the job site influence fuel consumption. Uneven or difficult terrain increases fuel use due to added engine load and maneuvering challenges (Hong & Lü, 2022). Harsh weather conditions, such as extreme heat or rain, can reduce equipment efficiency and raise fuel consumption (Hong & Lü, 2022). Job site congestion or limited space often leads to inefficient routing and idling, which increases fuel use (Zhou et al., 2022). Conversely, smooth and stable terrain supports more efficient operations and reduces fuel consumption (Kumar et al., 2021). The fifth part highlights how operator background influences fuel efficiency. Formal training equips operators with techniques that reduce fuel consumption during equipment use (Al-Hussein et al., 2020). Years of experience help operators make informed decisions that improve fuel management (Kumar et al., 2021). Confidence in applying fuel-saving practices also contributes to consistent and efficient operations (Zhou et al., 2022). The last part captures the operator's self-assessment of their fuel-saving performance. It reflects the belief that individual operating habits directly influence fuel efficiency, emphasizing the importance of awareness and behavior in achieving optimal fuel use (Hong & Lü, 2022).

In addition to the structured questionnaire, the study incorporated a qualitative component to capture deeper insights from equipment operators regarding fuel-saving practices. This was done through an open-ended question posed in the local dialect: "As operator, sa unsa nga paagi o sitwasyon man ta maka tipid gyud sa krudo sa pag operate?" which translates to "As an operator, in what ways or situations can we truly save fuel during operations?" Clarificatory follow-up questions were asked when necessary to ensure that responses were well understood and contextually rich. This approach allowed participants to express practical strategies and experiences in their own words, enhancing the depth and cultural relevance of the data collected.

Data Collection Procedure

The data collection process was conducted using paper-based questionnaires, which were deemed more convenient for the respondents. Distribution typically occurred during break periods when operators were more relaxed and receptive, allowing them to complete the instrument in approximately ten minutes. Participation was entirely voluntary, and respondents were informed of the study's purpose, their rights, and the confidentiality of their responses. Ethical protocols were strictly observed throughout the process, including the securing of informed consent and the protection of personal data.

Data Analysis

For data analysis, descriptive statistics were employed to summarize the demographic characteristics and operational profiles of the respondents, providing a clear overview of the sample. To examine the relationships between fuel consumption efficiency and five identified independent variables—namely operator behavior, equipment maintenance practices, equipment condition, worksite environment, and operator experience—a simple regression analysis was conducted. This inferential technique allowed the researchers to assess the predictive strength of each variable in relation to fuel efficiency. All statistical computations and visualizations were performed using Microsoft Excel, which offered a practical and accessible platform for managing and analyzing the data.

Ethical Considerations

Ethical considerations were central to the conduct of this study. Participants were assured of anonymity, and all data were handled in accordance with established ethical standards for research involving human subjects, as outlined by the American Psychological Association Ethics Code (APA, 2017). The study emphasized voluntary participation, with respondents fully informed about the purpose of the research, their right to withdraw at any time, and the confidentiality of their responses. Questionnaires were administered only after obtaining informed consent, and clarifications were provided when necessary to ensure understanding. Where applicable, approval from a relevant institutional ethics review board was secured prior to data collection. All personal data were protected through secure handling and storage procedures, ensuring compliance with ethical guidelines throughout the research process.

Results and Discussions

Ratings of Fuel Consumption Influencing Factors

Table 1 presents the mean scores and corresponding interpretations of five key independent variables influencing fuel consumption efficiency in construction equipment operations. These include Operator Behavior, Equipment Maintenance Practices, Equipment Condition, Worksite Environment, and Operator Training and Experience. Each variable comprises several criteria rated on a 5-point scale, with interpretations ranging from “Never Observed” to “Always Observed.” Understanding these behavioral and environmental factors is essential for optimizing fuel efficiency and productivity in construction settings (Volvo Construction Equipment, 2012; Hajare and Joshi, 2020).

Table 1 Mean Scores and Interpretation of Operator Behavior, Equipment Maintenance, and Related Variables

Independent Variables	**Mean Scores**	**Interpretation**
Operator Behavior		
1. Idle Shutdown	4.30	Always Observed
2. Acceleration Control	4.23	Always Observed
3. Procedure Adherence	4.30	Always Observed
4. Route Planning	4.47	Always Observed
Average	4.33	Always Observed
Equipment Maintenance Practices		
5. Scheduled Maintenance	4.50	Always Observed
6. Preventive Checks	4.43	Always Observed
7. Fuel System Care	4.30	Always Observed
8. Issue Reporting	4.50	Always Observed
Average	4.43	Always Observed
Equipment Condition		
9. Equipment Condition	4.37	Always Observed
10. Age Impact	4.00	Frequently Observed
11. Engine Efficiency	4.20	Frequently Observed
12. Fuel Reliability	4.47	Always Observed
Average	4.26	Always Observed
Worksite Environment		
13. Terrain Effect	4.23	Always Observed
14. Weather Impact	3.63	Frequently Observed
15. Site Congestion	3.60	Frequently Observed
16. Stable Terrain	4.10	Frequently Observed
Average	3.89	Frequently Observed
Operator Training and Experience		
17. Formal training	3.90	Frequently Observed
18. Experience level	3.93	Frequently Observed
19. Fuel-saving confidence	4.07	Frequently Observed
Average	3.97	Frequently Observed
20. Fuel Consumption Efficiency	**3.83**	**Frequently Observed**

Note. Interpretation of mean scores: 1.00–1.80 = Never Observed; 1.81–2.60 = Seldom Observed; 2.61–3.40 = Occasionally Observed; 3.41–4.20 = Frequently Observed; 4.21–5.00 = Always Observed. Adapted from Warmbrod (2014).

The data reveal that Operator Behavior and Equipment Maintenance Practices are consistently "Always Observed," with average scores of 4.33 and 4.43, respectively. This suggests strong adherence to fuel-saving practices such as idle shutdown, acceleration control, and scheduled maintenance. Equipment Condition also shows high observance (M = 4.26), though some criteria like engine efficiency and age impact are only "Frequently Observed." In contrast, Worksite Environment and Operator Training and Experience average lower scores (M = 3.89 and M = 3.97), indicating that external conditions and human factors may present variability in fuel-saving behavior. The overall score for Fuel Consumption Efficiency is 3.83, interpreted as "Frequently Observed," suggesting room for improvement despite strong behavioral and maintenance practices.

These findings underscore the importance of holistic strategies that go beyond operator discipline and maintenance routines. While technical adherence is high, environmental and experiential factors still influence fuel efficiency outcomes. Recent studies emphasize that operator skill level, site layout, and equipment age significantly affect fuel consumption and productivity (Hajare and Joshi, 2020). Therefore, targeted interventions such as terrain-specific planning, weather adaptation strategies, and enhanced training programs could further optimize fuel use and reduce emissions (Association of Equipment Manufacturers, 2023).

Operator Behavior Influence on Fuel Consumption Efficiency

Table 1 presents the regression statistics for a model examining the relationship between Operator Behavior and Fuel Consumption Efficiency in construction equipment operations. This analysis aims to quantify the extent to which behavioral factors—such as idle shutdown, acceleration control, and route planning—predict

fuel-saving outcomes. Understanding this relationship is crucial for improving operational efficiency and reducing environmental impact in construction settings (Volvo Construction Equipment, 2012).

Table 2 Regression Statistics: The Effect of Operator Behavior on Fuel Consumption Efficiency

Statistic	**Value**
Multiple R	0.207
R Square	0.043
Adjusted R Square	0.009
Standard Error	1.309
Observations	30

The regression model yielded a Multiple R of 0.207, indicating a weak positive correlation between operator behavior and fuel consumption efficiency. The R Square value of 0.043 suggests that only 4.3% of the variance in fuel efficiency can be explained by operator behavior alone. The Adjusted R Square drops to 0.009, reflecting minimal explanatory power when accounting for sample size and model complexity. With a standard error of 1.309 and 30 observations, the model highlights the limited predictive strength of operator behavior in isolation. Moreover, while operator behavior contributes to fuel efficiency, the low R^2 values suggest that other factors—such as equipment condition, terrain, and training—play a more substantial role (Volvo Construction Equipment, 2012). This aligns with recent findings that emphasize the importance of integrating sensor-based monitoring and machine learning models to capture the multifaceted nature of fuel consumption (Pereira, et al., 2021). Future models should consider a broader set of variables to improve predictive accuracy and support real-time decision-making in construction operations (Pereira, et al., 2021).

Table 3 presents the results of an Analysis of Variance (ANOVA) conducted to evaluate the statistical significance of the regression model examining the effect of Operator Behavior on Fuel Consumption Efficiency. ANOVA is used to determine whether the observed relationship between the independent and dependent variables is likely due to chance or reflects a meaningful pattern in the data (Volvo Construction Equipment, 2012).

Table 3 ANOVA Results: Assessing the Effect of Operator Behavior on Fuel Consumption Efficiency

Source	**df**	**SS**	**MS**	**F**	**Sig.**
Regression	1	2.155	2.155	1.257	0.272
Residual	28	48.012	1.715		
Total	29	50.167			

Note. ANOVA table for the regression model. Sig. refers to the significance level (p-value)

The ANOVA results show that the regression model has an F-value of 1.257 and a p-value (Sig.) of 0.272, which exceeds the conventional threshold of 0.05 for statistical significance. This indicates that the model does not significantly predict fuel consumption efficiency based on operator behavior alone. The Sum of Squares (SS) values show that most of the variation is attributed to the residuals (48.012), while the regression accounts for only a small portion (2.155), further supporting the limited explanatory power of the model. Moreover, these results suggest that while operator behavior may influence fuel efficiency, it is not a strong standalone predictor. Other factors—such as equipment condition, terrain, and idle time management—likely play a more substantial role (Volvo Construction Equipment, 2012). Recent studies emphasize the need for multi-variable models and sensor-based monitoring systems to capture the full complexity of fuel consumption dynamics in construction operations (Volvo Construction Equipment, 2012).

Table 4 displays the regression coefficients for a model assessing the predictive power of Operator Behavior on Fuel Consumption Efficiency. This analysis provides insight into the direction, strength, and statistical significance of the relationship between the independent variable (Operator Behavior) and the dependent variable (Fuel Efficiency), using unstandardized coefficients and confidence intervals.

Table 4 Regression Coefficients: Predicting Fuel Consumption Efficiency from Operator Behavior

Variable	**B**	**SE**	**t**	**p**	**Lower 95%**	**Upper 95%**	**Significance**
Intercept	-2.247	1.435	1.566	0.129	-0.693	5.187	No
Operator Behavior	0.367	0.327	1.121	0.272	-0.303	1.037	No

Note. B = unstandardized coefficient; SE = standard error; t = t-statistic; p = p-value. Significance is determined at $p < .05$.

The regression coefficient for Operator Behavior is B = 0.367, indicating a positive relationship with fuel efficiency—suggesting that improved operator behavior is associated with increased fuel efficiency. However, the p-value of 0.272 exceeds the 0.05 threshold, indicating that this relationship is not statistically significant. The 95% confidence interval ranges from -0.303 to 1.037, which includes zero, further confirming the lack of significance. The intercept is also not significant ($p = 0.129$), suggesting that the model does not reliably predict fuel efficiency when operator behavior is at its baseline. Furthermore, these results imply that operator behavior alone may not be a sufficient predictor of fuel consumption efficiency. This aligns with recent findings that emphasize the need to incorporate multiple variables, such as equipment condition, terrain, and environmental factors, to improve predictive accuracy (Ashqar, et al., 2024). Studies using more comprehensive models—including machine learning techniques—have demonstrated significantly better performance in forecasting fuel consumption by accounting for a broader range of operational parameters (Ashqar, et al., 2024).

Equipment Maintenance Practices Influence on Fuel Consumption Efficiency

Understanding the relationship between equipment maintenance practices and fuel efficiency is essential in optimizing operational costs and promoting sustainable practices in construction and industrial sectors. Regression analysis is a common statistical method used to explore this relationship by quantifying the strength and direction of association between variables. Table 5 presents the regression statistics from a study involving 30 observations, aiming to determine how well maintenance practices predict fuel efficiency outcomes.

Table 5 Regression Analysis of Equipment Maintenance Practices and Fuel Efficiency

Statistic	**Value**
Multiple R	0.238
R Square	0.057
Adjusted R Square	0.023
Standard Error	1.300
Observations	30

The regression results indicate a Multiple R of 0.238, suggesting a weak positive correlation between maintenance practices and fuel efficiency. The R Square value of 0.057 implies that only 5.7% of the variance in fuel efficiency can be explained by the maintenance practices measured in this model. The Adjusted R Square of 0.023 further confirms the limited explanatory power after adjusting for the number of predictors. The Standard Error of 1.300 indicates the average distance that the observed values fall from the regression line, which is relatively high given the scale of measurement. These results suggest that while there may be a slight positive trend, maintenance practices alone are not strong predictors of fuel efficiency in this sample. Moreover, the findings imply that while equipment maintenance is important, it may not be the sole or primary factor influencing fuel efficiency. Other variables—such as operator behavior, equipment type, workload, and environmental conditions—might play more significant roles. This highlights the need for a more comprehensive model that includes multiple predictors to better understand and improve fuel efficiency outcomes. Recent studies emphasize the integration of predictive maintenance with advanced analytics to enhance operational efficiency and reduce fuel consumption (Viana et al., 2025).

Analysis of Variance (ANOVA) is a statistical method used to determine whether the regression model significantly explains the variation in the dependent variable—in this case, fuel efficiency—based on the independent variable, equipment maintenance practices. Table 6 presents the ANOVA results for a regression model using 30 observations, aiming to assess whether maintenance practices have a statistically significant effect on fuel efficiency.

Table 6 ANOVA Results for the Regression Model on Equipment Maintenance and Fuel Efficiency

	df	**SS**	**MS**	**F**	**Significance F**
Regression	1	2.850	2.850	1.686	0.205
Residual	28	47.317	1.690		
Total	29	50.167			

Note. ANOVA table for the regression model examining the effect of Maintenance Practices

The F-statistic of 1.686 and a Significance F value of 0.205 indicate that the regression model is not statistically significant at conventional levels (e.g., $p < 0.05$). This means that the variation in fuel efficiency explained by maintenance practices is not strong enough to rule out the possibility that it occurred by chance. The Sum of Squares (SS) values show that the majority of variation lies in the residuals (47.317), while only a small portion is explained by the regression (2.850), reinforcing the weak explanatory power of the model. Furthermore, these results suggest that equipment maintenance practices, as measured in this study, do not significantly predict fuel efficiency. This finding aligns with recent literature emphasizing the need for more sophisticated approaches—such as predictive maintenance using artificial intelligence—to capture the complex factors influencing fuel consumption (Mahale, et al., 2025). Organizations may need to integrate sensor data, operator behavior, and environmental conditions into their models to achieve more accurate and actionable insights.

Regression coefficient analysis provides insight into the specific contribution of each predictor variable to the outcome—in this case, fuel efficiency. Table 7 presents the coefficients for a simple linear regression model examining the effect of equipment maintenance practices on fuel efficiency. This analysis helps determine whether maintenance practices significantly influence fuel consumption and whether the relationship is statistically meaningful variable to the outcome—in this case, fuel efficiency. Table 7 presents the coefficients for:

Table 7 Regression Coefficients for Predicting Fuel Efficiency from Maintenance Practices

	Coefficient	**Standard Error**	**t Stat**	**P-value**	**Lower 95%**	**Upper 95%**	**Significant**
Intercept	-1.388	1.898	0.731	0.471	-2.500	5.276	No
Maintenance Practices	0.552	0.425	1.299	0.205	-0.318	1.422	No

Note. Regression coefficients for the model predicting the dependent variable from Maintenance Practices. Significance is based on p < .05.

The intercept is -1.388, with a p-value of 0.471, indicating it is not statistically significant. The coefficient for Maintenance Practices is 0.552, suggesting a positive relationship with fuel efficiency; however, the p-value of 0.205 shows that this effect is not statistically significant at the conventional threshold of p < .05. The 95% confidence interval ranges from -0.318 to 1.422, which includes zero, further confirming the lack of significance. These results imply that, based on this model, maintenance practices do not have a statistically reliable impact on fuel efficiency. Moreover, the lack of statistical significance suggests that maintenance practices, as currently measured, may not be sufficient alone to predict fuel efficiency. This aligns with recent findings that emphasize the need for more advanced, data-driven approaches—such as predictive maintenance using machine learning—to capture the multifactorial nature of fuel consumption (Ferreira et al., 2021). Organizations should consider integrating sensor data, operational context, and machine learning models to enhance predictive accuracy and optimize fuel use.

Equipment Condition Influence on Fuel Consumption Efficiency

Regression analysis is a valuable tool for evaluating how specific factors, such as equipment condition, influence fuel efficiency. Table 8 presents the regression statistics for a model using 30 observations to assess the predictive power of equipment condition on fuel consumption. This analysis helps determine whether equipment condition is a meaningful variable in explaining variations in fuel efficiency.

Table 8 Regression Statistics for Predicting Fuel Efficiency from Equipment Condition

Statistic	**Value**
Multiple R	0.2599
R Square	0.0675
Adjusted R Square	0.0342

Statistic	Value
Standard Error	1.2925
Observations	30

Note. This table presents the regression statistics for the model predicting the dependent variable from Equipment Condition

The Multiple R value of 0.2599 indicates a weak positive correlation between equipment condition and fuel efficiency. The R Square value of 0.0675 suggests that only 6.75% of the variance in fuel efficiency is explained by equipment condition. The Adjusted R Square of 0.0342, which accounts for the number of predictors, confirms the limited explanatory power of the model. The Standard Error of 1.2925 reflects the average deviation of observed values from the regression line, indicating moderate variability. Overall, these results suggest that equipment condition has a weak and statistically insignificant influence on fuel efficiency in this sample. Furthermore, the findings imply that while equipment condition may contribute to fuel efficiency, it is not a strong standalone predictor. This supports recent research advocating for more comprehensive predictive maintenance models that incorporate multiple variables—such as sensor data, operational context, and machine learning algorithms—to improve accuracy and reliability (Viana et al., 2025). Organizations aiming to optimize fuel efficiency should consider integrating condition monitoring with advanced analytics to capture the full complexity of equipment performance.

Analysis of Variance (ANOVA) is used to determine whether a regression model significantly explains the variation in a dependent variable—in this case, fuel efficiency—based on an independent variable, equipment condition. Table 9 presents the ANOVA results for a model using 30 observations, assessing whether equipment condition has a statistically significant effect on fuel consumption.

Table 9 ANOVA Results for the Regression Model on Equipment Condition and Fuel Efficiency

	df	SS	MS	F	Significance F
Regression	1	3.3876	3.3876	2.0277	0.1655
Residual	28	46.7791	1.6707		
Total	29	50.1667			

Note. ANOVA table shows the variance analysis for the regression model

The F-statistic of 2.0277 and a Significance F value of 0.1655 indicate that the regression model is not statistically significant at the conventional threshold of $p < .05$. This means that the variation in fuel efficiency explained by equipment condition is not strong enough to rule out the possibility that it occurred by chance. The Sum of Squares (SS) values show that most of the variation lies in the residuals (46.7791), while only a small portion is explained by the regression (3.3876), reinforcing the weak explanatory power of the model. Moreover, these results suggest that equipment condition, as measured in this study, does not significantly predict fuel efficiency. This aligns with recent research emphasizing the need for more advanced predictive maintenance strategies that incorporate multiple variables—such as sensor data, operational metrics, and AI-driven analytics—to better understand and optimize fuel consumption (Mahale, et al., 2025). Relying solely on basic condition metrics may overlook critical factors influencing fuel efficiency.

Regression coefficient analysis helps determine the specific influence of predictor variables—in this case, equipment condition—on a dependent variable such as fuel efficiency. Table 10 presents the regression coefficients, standard errors, t-values, p-values, and confidence intervals for a model using equipment condition as the sole predictor. This analysis is essential for understanding whether equipment condition significantly contributes to variations in fuel consumption.

Table 10 Regression Coefficients for Predicting Fuel Efficiency from Equipment Condition

	Coefficient	**Standard Error**	**t Stat**	**P-value**	**Lower 95%**	**Upper 95%**	**Significant**
Intercept	-1.4015	1.6273	-0.9467	0.3519	-1.7929	4.8740	No
Equipment Condition	0.5384	0.3781	1.4240	0.1655	-0.2361	1.3130	No

Note. This table presents the regression coefficients, standard errors, t-values, p-values, and confidence intervals for the predictor.

The intercept is -1.4015 with a p-value of 0.3519, indicating it is not statistically significant. The coefficient for Equipment Condition is 0.5384, suggesting a positive relationship with fuel efficiency. However, the p-value of 0.1655 and the 95% confidence interval ranging from -0.2361 to 1.3130 indicate that this effect is not statistically significant at the conventional threshold of $p < .05$. These results suggest that equipment condition, as measured in this model, does not reliably predict fuel efficiency. Moreover, the lack of statistical significance implies that equipment condition alone may not be a sufficient predictor of fuel efficiency. This supports recent research advocating for more sophisticated predictive maintenance models that integrate multiple variables—such as vibration data, lubricant analysis, and operational metrics—alongside machine learning techniques to improve accuracy and reliability (Viana et al., 2025). Relying solely on basic condition metrics may overlook critical factors influencing fuel consumption.

Worksite Environment Influence on Fuel Consumption Efficiency

Regression analysis is a key method for evaluating how environmental factors at the worksite influence fuel efficiency. Table 11 presents the regression statistics for a model using 30 observations to assess the predictive power of the worksite environment on fuel consumption. This analysis helps determine whether environmental conditions at the worksite significantly contribute to variations in fuel efficiency.

Table 11 Regression Statistics for Predicting Fuel Efficiency from Worksite Environment

Statistic	**Value**
Multiple R	0.189
R Square	0.036
Adjusted R Square	0.001
Standard Error	1.314
Observations	30

Note. This table presents the regression statistics for the model predicting the dependent variable from Worksite Environment.

The Multiple R value of 0.189 indicates a weak positive correlation between worksite environment and fuel efficiency. The R Square value of 0.036 suggests that only 3.6% of the variance in fuel efficiency is explained by the worksite environment. The Adjusted R Square of 0.001, which accounts for the number of predictors, confirms the minimal explanatory power of the model. The Standard Error of 1.314 reflects moderate variability in the data. These results suggest that the worksite environment, as measured in this model, has a weak and statistically insignificant influence on fuel efficiency. Moreover, the findings imply that while the worksite environment may play a role in fuel efficiency, it is not a strong standalone predictor. This supports recent research indicating that environmental factors must be considered alongside operational, technical, and behavioral variables to effectively model energy efficiency outcomes (Shen et al., 2024). A more integrated approach—such as combining environmental data with predictive analytics and machine learning—may yield better insights for optimizing fuel use in industrial settings.

Analysis of Variance (ANOVA) is a statistical method used to determine whether a regression model significantly explains the variation in a dependent variable—in this case, fuel efficiency—based on an independent variable, the worksite environment. Table 12 presents the ANOVA results for a model using 30 observations, assessing whether worksite conditions significantly affect fuel consumption.

Table 12 ANOVA Results for the Regression Model on Worksite Environment and Fuel Efficiency

Source	**df**	**SS**	**MS**	**F**	**Sig.**
Regression	1	1.793	1.793	1.038	0.317
Residual	28	48.374	1.728		
Total	29	50.167			

Note. ANOVA table for the regression model examining the effect of Worksite Environment.

The F-statistic of 1.038 and a Significance (p-value) of 0.317 indicate that the regression model is not statistically significant at the conventional threshold of $p < .05$. This means that the variation in fuel efficiency explained by the worksite environment is not strong enough to rule out the possibility that it occurred by chance. The Sum of Squares (SS) values show that most of the variation lies in the residuals (48.374), while only a small portion is explained by the regression (1.793), reinforcing the weak explanatory power of the model. Moreover, these results suggest that the worksite environment, as measured in this study, does not significantly predict fuel efficiency. This finding aligns with recent research indicating that environmental factors alone are insufficient to explain variations in industrial energy efficiency. Instead, integrated models that combine environmental, operational, and regulatory variables are recommended for more accurate predictions (Shen et al., 2024).

Regression coefficient analysis is a fundamental method for evaluating the specific contribution of predictor variables—in this case, the worksite environment—to a dependent variable such as fuel efficiency. Table 13 presents the regression coefficients, standard errors, t-values, p-values, and confidence intervals for a model using worksite environment as the sole predictor. This analysis helps determine whether worksite conditions significantly influence fuel consumption.

Table 13 Regression Coefficients for Predicting Fuel Efficiency from Worksite Environment

Variable	**B**	**SE**	**t**	**p**	**Lower 95%**	**Upper 95%**	**Significance**
Intercept	-1.401	1.485	-0.944	0.353	-4.444	1.641	No
Worksite Environment	0.402	0.395	1.019	0.317	-0.406	1.211	No

Note. Regression coefficients for the model predicting the dependent variable from Worksite Environment. SE = Standard Error.

The intercept is -1.401 with a p-value of 0.353, indicating it is not statistically significant. The coefficient for Worksite Environment is 0.402, suggesting a weak positive relationship with fuel efficiency. However, the p-value of 0.317 and the 95% confidence interval ranging from -0.406 to 1.211 indicate that this effect is not statistically significant at the conventional threshold of $p < .05$. These results suggest that worksite environment, as measured in this model, does not reliably predict fuel efficiency. Furthermore, the lack of statistical significance implies that worksite environment alone may not be a sufficient predictor of fuel efficiency. This supports recent research advocating for more comprehensive models that integrate environmental, economic, and operational variables to better understand energy efficiency outcomes. Studies using advanced regression techniques, such as partially linear functional-coefficient models, have shown that environmental factors interact with economic conditions in complex ways that affect industrial energy efficiency (Shen et al., 2024).

Operator Experience and Training Influence on Fuel Consumption Efficiency

Operator experience and training are widely recognized as critical factors influencing equipment performance and fuel efficiency. Table 14 presents the regression statistics for a model using 30 observations to evaluate how well operator-related variables predict fuel consumption outcomes. This analysis provides insight into the extent to which human factors contribute to operational efficiency.

Table 14. Regression Statistics for Predicting Fuel Efficiency from Operator Experience and Training

Statistic	**Value**
Multiple R	0.5579
R Square	0.3113
Adjusted R Square	0.2867
Standard Error	1.1108
Observations	30

Note. This table presents the regression statistics for the model predicting the dependent variable from Operator Experience and Training.

The Multiple R value of 0.5579 indicates a moderate positive correlation between operator experience/training and fuel efficiency. The R Square value of 0.3113 suggests that approximately 31.13% of the variance in fuel efficiency is explained by this predictor. The Adjusted R Square of 0.2867 confirms the model's robustness after accounting for the number of predictors. The Standard Error of 1.1108 reflects relatively lower variability compared to previous models, indicating a better fit. These results suggest that operator experience and training have a meaningful and statistically relevant impact on fuel efficiency. Moreover, the findings underscore the importance of investing in operator training programs and experience-building initiatives to enhance fuel efficiency. This aligns with recent research showing that data-driven assessments of driver behavior and training can significantly improve fuel economy and operational safety (Kumar et al., 2025). Organizations should consider integrating behavioral analytics and continuous training to optimize performance and reduce fuel costs.

Analysis of Variance (ANOVA) is used to determine whether a regression model significantly explains the variation in a dependent variable—in this case, fuel efficiency—based on an independent variable, operator experience and training. Table 15 presents the ANOVA results from a model using 30 observations, evaluating whether this human factor significantly contributes to fuel consumption outcomes.

Table 15 ANOVA Results for the Regression Model on Operator Experience and Training

	df	**SS**	**MS**	**F**	**Significance F**
Regression	1	15.6165	15.6165	12.6558	0.0014
Residual	28	34.5502	1.2339		
Total	29	50.1667			

Note. ANOVA table shows the variance explained by the regression model and the residual variance

The F-statistic of 12.6558 and a Significance F value of 0.0014 indicate that the regression model is statistically significant at the conventional threshold of $p < .05$. This means that operator experience and training explain a meaningful portion of the variation in fuel efficiency. The Sum of Squares (SS) values show that a substantial portion of the variance (15.6165) is attributed to the regression, while the residual variance (34.5502) is comparatively lower, reinforcing the strength of the model. Furthermore, these results highlight the importance of operator experience and training in improving fuel efficiency. This supports recent research showing that well-trained operators can significantly reduce fuel consumption through better handling, decision-making, and adherence to operational protocols (Kumar et al., 2025). Organizations should prioritize structured training programs and continuous skill development to enhance both performance and sustainability.

Regression coefficient analysis provides detailed insights into the strength and significance of individual predictors in a model. Table 16 presents the regression coefficients for a model examining the effect of operator experience and training on fuel efficiency. This analysis helps determine whether human factors significantly influence fuel consumption outcomes.

Table 16. Regression Coefficients for Predicting Fuel Efficiency from Operator Experience and Training

	Coefficient	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Significant
Intercept	-1.4015	1.4854	-0.9435	0.3535	-4.4442	1.6412	No
Operator Experience	1.3197	0.3710	3.5575	0.0014	0.5598	2.0796	Yes

Note. Coefficients table presents the regression weights, standard errors, t statistics, p-values, and confidence intervals for each predictor.

Among the five predictors, only Operator Experience and Training yielded a statistically significant result ($p = 0.0014$), indicating a strong and reliable relationship with fuel efficiency. All other variables—Operator Behavior ($p = 0.272$), Maintenance Practices ($p = 0.205$), Equipment Condition ($p = 0.1655$), and Worksite Environment ($p = 0.317$)—were found to be not statistically significant, suggesting that they do not independently explain a meaningful portion of the variance in fuel efficiency within the context of this study. Furthermore, these findings highlight the critical role of human capital—specifically, operator experience and training—in improving fuel efficiency. While technical and environmental factors are often emphasized, this result supports a growing body of research that underscores the value of behavioral and experiential competencies in operational performance. Organizations should prioritize structured training programs and continuous learning to enhance fuel efficiency and reduce operational costs (Kumar et al., 2025).

Themes from the Interviews with Operators on Fuel Efficiency

The question asked to operators was: "As operator, sa unsa nga paagi o sitwasyon man ta maka tipid gyud sa krudo inig operate?"

English translation: "As an operator, in what ways or situations can we truly save fuel during operation?"

From the responses, five key themes emerged that reflect the practical knowledge and experience of operators in managing fuel consumption.

The first theme is Fuel Efficiency. Operators are highly aware of how task conditions affect fuel use. One operator shared, "Kung humok ra ang yuta sir o kun dili gaan ra ang trabahoon maka tipid gyud ta sa krudo ana kay dili man taas ang RPM sa makina," meaning "If the soil is soft or the task is light, we can save fuel because the engine RPM doesn't need to be high." They also mentioned using neutral gear when going downhill to reduce fuel use, but warned that this should be done cautiously when the equipment is loaded. This leads to the follow-up question: Unsa pa nga klase sa trabaho ang inyong nabantayan nga makaminos sa krudo? (What other types of tasks have you noticed help reduce fuel consumption?)

The second theme is Engine RPM Management. Operators consistently emphasized the importance of controlling RPM to match the workload. One noted, "Kung waiting ra ug walay buhatunon i-Low ang rpm or kung mahimo pagngon gyud ang makina," which translates to "If just waiting and there's nothing to do, lower the RPM or turn off the engine if possible." This practice helps avoid unnecessary fuel use. A clarifying question here is: Kanus-a ninyo giconsider nga i-off ang makina kaysa i-low lang ang RPM? (When do you decide to turn off the engine instead of just lowering the RPM?)

The third theme is Idle and Standby Practices. Operators recommend turning off equipment during idle times to save fuel and reduce wear. One shared, "Pagngon ang ekipo nya paandaron ra ug balik na operation para makapahuway makina ug gamay ra konsumo," meaning "We turn off the equipment and restart it only when needed, allowing the engine to rest and consume less fuel." This raises the question: Unsa kadugay nga standby ang inyong gi-consider nga angay na i-off ang makina? (How long does standby need to be before you decide to turn off the engine?)

The fourth theme is Equipment Condition. Operators noted that newer units perform better and require less fuel. One explained, "Kung bag-o kusgan pa kaayo ang makina ug pump dili pa nato need magpasaka ug RPM," or "If the unit is new, the engine and pump are still strong, so we don't need to increase the RPM." This leads to the question: Giunsa ninyo pag-adjust sa inyong operation kung daan na ang unit? (How do you adjust your operation when the unit is older or less efficient?)

Finally, the fifth theme is Operator Judgment. Operators rely on experience and situational awareness to make fuel-saving decisions. One stated, "Depende ra gyud na sa operator og gi unsa niya pag trabaho sir," which means "It really depends on the operator and how he does the work." Another added that crane operations vary—erection tasks save fuel due to standby, while hustling consumes more due to constant acceleration. A useful follow-up question is: Unsa nga mga kasinatian ang nakatabang ninyo sa pagdesisyon kung unsaon pagtipid sa krudo? (What experiences have helped you make better decisions about saving fuel during operations?)

Table 18 presents the alignment between the key determinants of fuel consumption efficiency identified through quantitative analysis and the thematic insights derived from operator interviews. It highlights how each determinant corresponds to specific practical themes, illustrating the interplay between measurable factors and operator experiences in influencing fuel efficiency.

Table 18. Alignment of Quantitative Determinants with Qualitative Themes on Fuel Consumption Efficiency

Determinants of Fuel Efficiency (Quantitative)	Aligned Themes from Operator Interviews (Qualitative)	Explanation
Operator Experience and Training	**Operator Judgment**	Operators emphasized that fuel-saving depends heavily on their experience, situational awareness, and decision-making. This theme aligns with the significant quantitative finding that operator experience/training strongly predicts fuel efficiency.

Determinants of Fuel Efficiency (Quantitative)	Aligned Themes from Operator Interviews (Qualitative)	Explanation
Operator Behavior	**Engine RPM Management - Idle and Standby Practices - Fuel Efficiency Strategies**	Specific behaviors such as adjusting engine RPM based on workload, shutting down equipment during idle, and using neutral gear on downhill slopes were frequently mentioned. These behaviors are part of the broader operator behavior determinant but were not statistically significant alone.
Equipment Maintenance Practices	**Equipment Condition**	Operators noted that well-maintained and newer equipment perform better and consume less fuel. This theme corresponds to maintenance and condition but these determinants were not statistically significant predictors in the regression analysis.
Equipment Condition	**Equipment Condition**	Operators discussed how newer units require less RPM and consume less fuel, while older units need operational adjustments. This aligns with the equipment condition determinant.
Worksite Environment	**Fuel Efficiency(Task Conditions)**	Operators mentioned how terrain softness, weather, and site congestion affect fuel use. This theme relates to the worksite environment determinant, which showed weak statistical influence.

The table shows that operator experience and training, the only statistically significant predictor, aligns closely with the theme of operator judgment, emphasizing the critical role of human decision-making. Other determinants such as operator behavior, equipment maintenance, equipment condition, and worksite environment correspond to themes reflecting practical strategies and contextual factors described by operators. While these latter determinants did not show strong independent statistical significance, their thematic alignment underscores their operational relevance and the complex, interdependent nature of fuel efficiency in construction equipment operations.

Common Elements: Alignment Between Themes and Regression Findings

One of the strongest points of convergence lies in the theme of Operator Experience and Training, which was the only statistically significant predictor of fuel efficiency in the regression analysis ($p = 0.0014$, $R^2 = 0.3113$). This aligns directly with the qualitative theme of Operator Judgment, where operators emphasized that fuel-saving decisions depend heavily on their experience, situational awareness, and task-specific strategies. Statements like "Depende ra gyud na sa operator og gi unsa niya pag trabaho sir" (It really depends on the operator and how he does the work) reflect this insight. Both data sources affirm that human decision-making is central to fuel efficiency.

Another area of alignment is the theme of Engine RPM Management, which was frequently mentioned by operators as a way to reduce fuel use. While not statistically significant in the regression model when isolated (as part of general operator behavior), this theme supports the idea that experienced operators intuitively manage RPM based on workload, which may be embedded within the broader construct of operator experience.

Diverging Elements: Gaps Between Operator Perceptions and Statistical Significance

Despite being frequently mentioned in interviews, Maintenance Practices, Equipment

Condition, and Worksite Environment were not statistically significant predictors in the regression analysis. Operators often discussed how newer equipment or well-maintained units consume less fuel, and how soft soil or light tasks reduce engine strain. For example, one operator noted, "Kung bag-o kusgan pa kaayo ang makina ug pump dili pa nato need magpasaka ug RPM." (If the unit is new, the engine and pump are still strong, so we don't need to increase the RPM.) However, these factors did not show strong predictive power in the quantitative model. This divergence may be due to the limited sample size (n = 30), the simplicity of the regression models, or the possibility that these factors interact with operator behavior in more complex ways not captured by single-variable analysis.

Similarly, Idle and Standby Practices were emphasized in the interviews as a key strategy for saving fuel, yet this behavior was not isolated as a significant variable in the regression. This suggests that while operators perceive these practices as effective, their impact may be more subtle or context-dependent, requiring more granular measurement or interaction modeling.

Synthesis of Themes and Regression Analysis Results

The convergence between operator experience and statistical significance validates the importance of operator experience and training in fuel efficiency. The determinant of operator experience and training strongly aligns with the qualitative theme of operator judgment, where operators emphasized that fuel-saving decisions rely heavily on their accumulated experience, situational awareness, and task-specific adaptations. However, the divergence in other areas suggests that operator perceptions, while valuable, may not always align with measurable outcomes unless contextualized within broader operational systems. This highlights the need for future studies to use more complex models (e.g., interaction terms, machine learning) and larger datasets to capture the nuanced relationships between technical, environmental, and human variables.

In summary, the qualitative and quantitative findings complement each other: the former provides depth and context, while the latter offers measurable validation. Together, they point to a clear direction—investing in operator training and experience is not only perceived as effective but is also statistically proven to enhance fuel efficiency. Meanwhile, technical and environmental factors, though important, may require more sophisticated modeling to fully understand their role.

Implications of the Findings

The integration of qualitative themes and quantitative regression findings reveals a compelling narrative about the central role of operator experience and judgment in achieving fuel efficiency in equipment operations. The regression analysis identified Operator Experience and Training as the only statistically significant predictor of fuel efficiency, explaining over 31% of the variance (Kumar et al., 2025). This quantitative result is strongly reinforced by the qualitative data, where operators consistently emphasized the importance of situational awareness, task-specific adjustments, and accumulated experience in making fuel-saving decisions.

Operators described strategies such as adjusting engine RPM based on workload, turning off equipment during idle periods, and using neutral gear on downhill slopes when safe. These practices reflect a deep, intuitive understanding of fuel-saving behaviors that are not easily captured by technical specifications alone. While themes like Maintenance Practices, Equipment Condition, and Worksite Environment were frequently mentioned in interviews, they did not emerge as statistically significant in the regression models. This divergence suggests that while these factors are operationally relevant, their impact on fuel efficiency may be indirect or dependent on how operators respond to them (Wang et al., 2024).

The implication is clear: technical improvements and environmental conditions alone are insufficient without operator experience and judgment. Organizations aiming to reduce fuel consumption should prioritize investments in operator training, continuous learning, and behavior-based performance monitoring (Yazdi, 2024). Moreover, future research should explore how these human factors interact with machine condition and environmental variables using more complex models and larger datasets (Shen et al., 2024). Ultimately, this study underscores that empowering operators with knowledge and experience is not just a supportive measure—it is a strategic necessity for sustainable and efficient operations.

Conclusion

This study found that among several operational factors, operator experience and training was the only statistically significant predictor of fuel efficiency, supported by both regression analysis and operator insights. Operators described fuel-saving strategies such as adjusting RPM, turning off engines during idle, and adapting techniques based on task and equipment condition—highlighting the importance of judgment and situational awareness. While maintenance practices, equipment condition, and worksite environment were frequently mentioned, they did not show statistical significance, suggesting their impact may be indirect or context-dependent. These findings emphasize that technical improvements alone are insufficient without operator experience and judgment.

Limitations include the small sample size and the use of linear models, which may not capture complex interactions. Future research should expand the dataset, use advanced modeling techniques, and explore how operator behavior interacts with environmental and mechanical factors. Investing in operator development remains essential for sustainable and efficient operations.

Acknowledgement

This study would not have been possible without the generous participation of the thirty construction equipment operators who shared their time, experience, and practical wisdom. Their insights—rooted in years of hands-on work—provided the foundation for both the statistical findings and the thematic depth of this research. The strategies they described, from intuitive fuel-saving techniques to context-specific adjustments, reflect the quiet expertise that drives efficiency on the ground.

This work is dedicated to the entire construction business community—workers, clients, contractors, and stakeholders—whose daily efforts shape the built environment. The findings affirm that fuel efficiency is not merely a technical goal but a human achievement. Skilled operators, empowered through training and supported by thoughtful monitoring, are essential to sustainable and effective operations. May this study serve as a reminder that investing in people is investing in progress.

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