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Original Article

Ranking the Drivers of Agricultural Machinery Maintenance Costs and Their Impacts on Rural Economic Sustainability in Western Iran

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Abstract

Purpose- This study aims to identify and rank the key drivers affecting agricultural machinery maintenance and repair costs and to examine their implications for strengthening the economic sustainability of rural areas in western Iran.

Design/methodology/approach- This study employs a mixed-methods research design integrating qualitative and quantitative approaches. In the qualitative phase, a systematic literature review and semi-structured interviews with 24 agricultural mechanization experts were conducted to identify and validate the main factors influencing maintenance and repair costs. In the quantitative phase, real maintenance records of 80 agricultural machines operating in the provinces of Kermanshah, Ilam, and Kurdistan were collected over a three-year period, resulting in 240 machine-year observations. The Extreme Gradient Boosting (XGBoost) algorithm was then applied to model the relationship between explanatory variables and maintenance costs and to rank the relative importance of factors based on the Gain criterion.

Findings- The findings demonstrate that maintenance and repair costs are influenced by the simultaneous interaction of technical, managerial, operational, human, and environmental factors. The XGBoost model achieved satisfactory predictive performance on the testing dataset, with an R^2 value of 0.86, RMSE of 39.4 million IRR, and MAE of 28.7 million IRR. The feature importance analysis revealed that machine age (18.9%), lack of preventive maintenance implementation (17.2%), and unfavorable operating conditions (15.1%) were the three most influential determinants of maintenance and repair costs, jointly accounting for more than half of the model's total importance. These findings indicate that machinery aging, insufficient maintenance planning, and improper operating practices represent the primary sources of increased maintenance expenditures. Furthermore, the results demonstrate that effective preventive maintenance programs, improved maintenance management systems, optimized spare parts management, and enhanced operator practices can reduce life-cycle machinery costs and contribute to rural economic sustainability.

Research limitations/implications- This study is limited by the geographical scope of the investigated provinces and the availability of historical maintenance records from agricultural machinery. Future research may expand the analysis to other regions and incorporate larger longitudinal datasets, economic variables, and advanced predictive approaches to further improve the understanding of machinery maintenance cost dynamics.

Originality/value- This study contributes to the agricultural mechanization and rural sustainability literature by integrating expert-based knowledge, real machine-year maintenance records, and machine-learning techniques within a unified analytical framework. Unlike previous studies that mainly relied on conventional statistical methods or examined individual factors separately, this research applies the XGBoost algorithm to quantify the relative importance of maintenance cost drivers and links machinery maintenance management with rural economic sustainability.

Keywords: Agricultural machinery, Maintenance and repair costs, XGBoost algorithm, Economic sustainability, Rural development, Agricultural mechanization.

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1. Introduction

Sustainable rural development has become a major global priority because of its critical role in ensuring food security, reducing rural poverty, and improving the quality of life in agricultural communities (Falchetta et al., 2024: 418). Since agriculture remains the principal economic activity in many rural regions, its productivity and efficiency directly influence rural economic sustainability (Yang et al., 2025: 396). Accordingly, improving agricultural productivity while reducing production costs has become an essential requirement for sustainable rural development (Rana et al., 2025: 3). Agricultural mechanization has contributed substantially to this objective by increasing operational efficiency, improving resource utilization, reducing labor requirements, and enhancing farm productivity (Salvati et al., 2025: 118). As a result, agricultural machinery represents one of the most valuable productive assets in modern farming systems and plays a crucial role in improving farmers' income and sustaining rural economies (He et al., 2025: 203).

Despite these benefits, maintenance and repair (M&R) of agricultural machinery remain major challenges for farmers and agricultural managers (Leslie, 2023: 9). Machinery reliability and operational efficiency depend heavily on effective maintenance practices, whereas inadequate maintenance increases equipment failures, production costs, and operational interruptions while reducing agricultural productivity (Shen et al., 2025: 222). In contrast, preventive and predictive maintenance programs improve machinery reliability, extend service life, minimize downtime, and reduce long-term maintenance expenditures (Soleimani et al., 2025: 441).

The importance of efficient maintenance management is particularly evident in Iran, where a considerable proportion of the agricultural machinery fleet is aging and operates under demanding field conditions (Karimikia & Mohammadi, 2025: 80). Rising machinery and spare-parts prices, limited access to specialized maintenance services, and increasing production costs have substantially increased maintenance expenditures for agricultural producers (Yousefi Taleghani et al., 2022: 167). Financial constraints frequently force farmers to postpone preventive maintenance and major repairs, leading to more frequent equipment failures, shorter machinery service life, and higher long-term repair costs (Pakzat & Rezvani, 2025: 266). Consequently, increasing maintenance expenditures reduce farm profitability, limit reinvestment opportunities, and weaken the economic sustainability of rural households (Seifollahi, 2026: 119).

Maintenance and repair costs constitute a substantial share of machinery operating expenses, including expenditures on spare parts, labor, servicing, repairs, machinery downtime, and indirect production losses (Wu et al., 2023: 512). Therefore, identifying the factors responsible for increasing maintenance costs has become an important scientific and managerial priority for improving machinery performance, enhancing agricultural productivity, and strengthening the long-term economic sustainability of rural communities (Rizzo et al., 2025: 348)

Despite the recognized importance of maintenance and repair (M&R) costs, decision-makers still face a fundamental challenge: determining which factors contribute most to increasing these costs and therefore deserve the highest managerial priority. In practice, agricultural machinery maintenance is influenced by numerous technical, managerial, operational, human, and environmental variables that interact simultaneously. However, because these factors rarely operate independently, identifying their relative contributions remains difficult. As a result, maintenance planning and investment decisions are often based on experience rather than objective evidence, leading to inefficient allocation of financial resources and higher machinery life-cycle costs. This problem is particularly important in western Iran, where aging machinery, limited financial resources, and increasing maintenance expenditures directly threaten the economic sustainability of rural production systems. Therefore, developing an evidence-based approach capable of identifying and ranking the principal drivers of maintenance and repair costs represents the central research problem addressed in this study.

Previous studies have shown that agricultural machinery maintenance and repair (M&R) costs are affected by a combination of technical, managerial, operational, and human factors.

Machinery age, operating conditions, equipment utilization, preventive maintenance implementation, spare-parts availability, operator skills, maintenance planning, and the adoption of modern maintenance technologies have consistently been identified as important determinants of maintenance performance (Karami & Khalilian, 2026; Takeshima, 2025; Fromjan, 2025; Martinez-Monro et al., 2024). More recent studies have further emphasized the contribution of maintenance management to agricultural productivity and economic performance. For example, Kedir Busse et al. (2026) demonstrated that machinery aging substantially increases repair costs and reduces operational efficiency, while Soltanali and Khojastehpour (2023) highlighted the importance of preventive maintenance, maintenance planning, and organizational support in improving maintenance performance. Likewise, Shen et al. (2025), Soleimani et al. (2025), Wang et al. (2024), and Hertwich et al. (2025) emphasized the growing role of intelligent technologies, data-driven maintenance, and advanced mechanization in improving equipment efficiency and supporting sustainable agricultural development.

Despite these valuable contributions, several important limitations remain. Most previous studies have examined technical, managerial, or operational factors separately, providing only a fragmented understanding of the mechanisms driving maintenance costs. In addition, conventional statistical techniques have been the dominant analytical approach, limiting the ability to capture complex nonlinear interactions among multiple influencing factors. Consequently, although the existing literature has identified numerous determinants of maintenance costs, it has provided limited evidence regarding their relative importance and their combined contribution to maintenance cost variation. Despite these valuable contributions, several important research gaps remain. First, previous studies have primarily relied on conventional statistical techniques or descriptive analyses, and no study has employed the Extreme Gradient Boosting (XGBoost) algorithm to rank the relative importance of the factors affecting agricultural machinery maintenance and repair costs. Second, although maintenance costs have been widely investigated from technical and engineering perspectives, their implications for the economic sustainability of rural areas have received little direct attention, and no previous research has explicitly linked maintenance cost drivers with rural economic sustainability within an integrated analytical framework. Third, most existing studies have relied on cross-sectional surveys, expert opinions, or experimental observations, whereas evidence based on real machine-year maintenance records remains largely absent. Consequently, there is still a lack of empirical studies that combine actual longitudinal machinery data with advanced machine-learning techniques to identify and prioritize the determinants of maintenance and repair costs. The present study addresses these gaps by integrating qualitative and quantitative evidence, employing real machine-year observations from agricultural machinery operating in western Iran, and applying the XGBoost algorithm to rank the key drivers of maintenance and repair costs while examining their implications for rural economic sustainability.

Recent advances in artificial intelligence and machine learning have created new opportunities for modelling complex agricultural systems. Among the available techniques, the Extreme Gradient Boosting (XGBoost) algorithm has become one of the most powerful predictive tools because of its high accuracy, ability to model nonlinear relationships, robustness in handling complex datasets, and capability to quantify the relative importance of explanatory variables (Khajeh et al., 2025: 39). These characteristics make XGBoost particularly suitable for identifying and prioritizing the principal drivers of agricultural machinery maintenance and repair costs while providing more reliable evidence for maintenance planning and managerial decision-making.

Against this background, the present study aims to identify and rank the factors affecting agricultural machinery maintenance and repair (M&R) costs using the Extreme Gradient Boosting (XGBoost) algorithm and to examine how these factors influence the economic sustainability of rural areas in western Iran. The study is based on real machine-year observations collected from agricultural machinery operating in the provinces of Kermanshah, Ilam, and Kurdistan, providing empirical evidence from actual maintenance records rather than experimental or perception-based data. By integrating qualitative findings, conventional statistical analyses, and machine-learning techniques within a unified analytical framework, this research offers a more comprehensive understanding of the determinants of maintenance and repair costs than has previously been available.

Accordingly, the study addresses the following research question: Which technical, managerial, operational, human, and environmental factors exert the greatest influence on agricultural machinery maintenance and repair costs, and what is the relative importance of each factor in explaining cost variation? Answering this question not only identifies the principal cost drivers but also provides a scientific basis for prioritizing maintenance interventions and allocating resources more effectively. Such evidence is expected to support the design of preventive maintenance strategies, optimize machinery replacement decisions, improve spare-parts management, strengthen the implementation of Computerized Maintenance Management Systems (CMMS), and ultimately reduce machinery life-cycle costs. Beyond its methodological contribution, this study has important practical implications. Reducing maintenance and repair costs can improve machinery availability, increase farm profitability, enhance farmers' capacity for reinvestment, and strengthen the resilience of agricultural production systems. These improvements contribute directly to the economic sustainability of rural communities by increasing production efficiency and supporting the long-term competitiveness of the agricultural sector. Therefore, the findings of this study provide valuable evidence for agricultural managers, extension organizations, and policymakers seeking to improve maintenance management practices and promote sustainable rural development in western Iran

2.Research Theoretical Literature

2.1. Asset Life Cycle Theory

Asset Life Cycle Theory is one of the fundamental frameworks in asset management and maintenance engineering. It is based on the premise that every industrial asset progresses through a series of identifiable stages throughout its lifetime, including design, procurement, installation, operation, maintenance, upgrading, and ultimately retirement or replacement (Freiberger et al., 2025: 201). The theory emphasizes that decisions made at each stage of the asset life cycle influence not only the technical performance of the equipment but also its total life-cycle cost (Weiss et al., 2024: 679). From this perspective, focusing solely on the initial acquisition cost often results in suboptimal decision-making because the majority of an asset's actual costs are incurred during its operation and maintenance phases (Wang et al., 2023: 446).

One of the leading scholars in this field is Andrew K. S. Jardine, whose life-cycle maintenance theory argues that maintenance strategies should be tailored to the specific stage of an asset's life cycle. According to Jardine, maintenance efforts during the early stages of an asset's life should emphasize condition monitoring and the prevention of premature failures, whereas decisions concerning refurbishment or replacement become increasingly important as the asset approaches the end of its useful life. His theory highlights the critical role of operational performance data in reducing life-cycle costs and extending the effective service life of physical assets (Jardine, 2023: 50-52).

Another prominent contributor is B. S. Dhillon, who expanded the concept of Life Cycle Engineering by emphasizing the integration of technical, economic, and managerial decisions throughout the entire life span of engineering assets (Dhillon, 2022: 69-70). Dhillon argues that maintenance and repair costs are determined by the combined effects of initial design, operating conditions, and maintenance management policies. He further maintains that scientifically informed interventions during the early stages of the asset life cycle can substantially reduce future maintenance expenditures. From his perspective, life-cycle asset management serves as a strategic approach to improving system reliability while minimizing long-term organizational costs (ibid: 87-88).

Overall, Asset Life Cycle Theory provides a comprehensive analytical framework for systematically examining the relationships among equipment characteristics, maintenance decisions, and repair costs over the entire service life of industrial assets.

2.2. Reliability and Maintainability Theory

Reliability and Maintainability Theory constitutes one of the principal theoretical foundations of systems engineering and maintenance management. The theory focuses on analyzing equipment failure behavior and its consequences for system performance and organizational costs.

Reliability refers to the probability that a component or system will perform its intended function under specified operating conditions for a defined period of time, whereas maintainability denotes the ease, speed, and effectiveness with which maintenance activities can restore the system to an operational state (Pilanawithana et al., 2024: 23-24). The theory assumes that increases in failure rates, equipment downtime, and maintenance complexity directly contribute to higher maintenance and repair costs (Marugan, 2023: 177).

One of the most influential scholars in this field is John Moubray, who introduced the Reliability-Centered Maintenance (RCM) framework and fundamentally transformed maintenance management practices. Moubray argued that not all equipment requires the same level of maintenance and that maintenance strategies should be designed according to the consequences of failure, operational risk, and the functional importance of equipment. Reliability-Centered Maintenance emphasizes identifying failure modes, analyzing the consequences of failures, and selecting the most appropriate maintenance policies with the objective of minimizing critical failures while effectively controlling maintenance costs (Moubray, 2023: 21-24).

Another notable contributor is Marvin Rausand, whose work on system reliability analysis and risk engineering has significantly advanced the field. By developing probabilistic reliability models, Rausand demonstrated how failure rates, mean time between failures, and repair times can be quantitatively modeled. He argues that reliability analysis is not only essential for improving system safety but also serves as an effective tool for predicting and controlling maintenance and repair costs (Rausand, 2023: 55-58). Within this theoretical framework, variables such as equipment age, operating conditions, the quality of preventive maintenance, workforce competency, and the implementation of computerized maintenance management systems (CMMS) are recognized as key determinants of maintenance and repair costs (Zaccarine et al., 2024: 381).

In summary, Reliability and Maintainability Theory provides a robust scientific foundation for understanding the relationship between equipment failures and maintenance expenditures.

In the present study, Asset Life Cycle Theory serves as the primary framework for analyzing the effects of the structural and temporal characteristics of agricultural machinery particularly equipment age and operational life stage on maintenance and repair costs. Reliability and Maintainability Theory, in turn, provides the conceptual basis for explaining how failure rates, operating conditions, preventive maintenance quality, and the effectiveness of maintenance support systems influence maintenance expenditures. The integration of these complementary theoretical perspectives enables a more comprehensive understanding of the interactions between the technical and operational characteristics of agricultural machinery and their economic consequences for rural producers. Finally, this theoretical framework is complemented by a machine learning approach based on the Extreme Gradient Boosting (XGBoost) algorithm, enabling a data-driven identification and prioritization of the factors influencing the economic sustainability of rural areas.

2.3. Empirical Literature Review

Kedir Busse et al. (2026), in a study entitled Evaluation and Optimization of Agricultural Machinery Management System Costs in the Arjo Didessa Sugar Factory, reported that among the inactive machines, 49% required minor repairs, while 14% were beyond repair and should be permanently removed from service. The predicted work rate exceeded the actual work rate by 35.33%. Among the agricultural operations examined, land clearing exhibited the smallest deviation from the actual work rate (5.73%), whereas row planting showed the largest deviation (67.21%). Although initial repair costs were relatively low, maintenance expenditures increased substantially as machinery aged. The optimization model implemented during the 2021–2022 cropping season reduced overall operating costs by 10.60%, highlighting the importance of accurately estimating actual machinery work rates and conducting performance analyses to improve operational efficiency. Karimikia and Mohammadi (2025), in their study entitled Identification and Ranking of Agricultural Machinery Productivity Indicators in the Horticultural and Crop Production Sectors of Chaharmahal and Bakhtiari Province, found that the most influential factor affecting agricultural machinery productivity was machinery design and its compatibility with cultivated land conditions. This was followed by optimal management and planning as the second most influential indicator. Among the six identified sub-criteria, operational performance (approximately 38%), suitability to local needs and conditions (15%), and machinery efficiency (14%) ranked first, second, and third, respectively. Within the second group of indicators, machinery efficiency (14%), proper machinery utilization (11.5%), and financial resource provision (7.8%) were identified as the most significant determinants. Karami & Khalilian (2025), in their study examining the impact of investment in agricultural machinery on the value added of Iran's agricultural sector, concluded that investment in agricultural machinery and equipment has a significant positive effect on agricultural production. Their findings indicate that increasing investment in mechanization directly contributes to higher agricultural output. Soltanali and Khojastehpour (2023), in a study on identifying and prioritizing the factors influencing effective maintenance management in agro-industrial enterprises, found that organizational management, human factors, and structural factors were the three most important dimensions of maintenance management. Furthermore, based on the Best–Worst Method (BWM), the sub-criteria top management support, allocation of maintenance budgets and optimized inventory management, and adoption of appropriate maintenance strategies received the highest overall weights of 0.108, 0.075, and 0.067, respectively. Shen et al. (2025), in their study entitled Cost–Benefit Analysis of Remanufacturing Used Agricultural Machinery Components in China and Its Implications for Agricultural Economic Prosperity, concluded that remanufacturing agricultural machinery components can substantially reduce production costs while improving productivity and farm profitability. Given the dependence of many rural regions in China on mechanized agriculture, expanding the remanufacturing industry can strengthen rural economies and create new employment opportunities in equipment maintenance and refurbishment. Consequently, remanufacturing represents not only an economically and environmentally sustainable strategy but also an effective instrument for promoting sustainable agricultural development and reducing regional economic disparities. Soleimani et al. (2025), in a systematic review entitled Artificial Intelligence in Agricultural Machinery and Robotics: A Systematic Review and Future Perspectives, concluded that artificial intelligence (AI) and machine learning significantly enhance the performance of agricultural machinery and intelligent robotic systems, particularly in the areas of detection, navigation, decision-making, and structural optimization. These technological improvements increase agricultural productivity, reduce production costs, enhance farmers' incomes, and strengthen rural agricultural value chains. The authors further argued that the continued adoption of intelligent mechanization technologies is expected to promote rural economic development by creating new employment opportunities in the maintenance, management, and operation of advanced agricultural systems while reducing dependence on traditional labor. Hertwich et al. (2025), in their critical assessment of the climate and resource-related costs and benefits of agricultural machinery and equipment in Southeastern European countries, concluded that agricultural mechanization should increasingly focus on improving machinery utilization efficiency, reducing resource consumption, and promoting low-carbon technologies in order to enhance rural economic performance while ensuring the sustainability of agricultural production systems. Wang et al. (2024), in their investigation of the impact of modern agricultural machinery on agricultural economic development in eastern China, found that modern mechanization significantly improves machinery performance in uneven and sloping agricultural lands. Through higher operational efficiency, reduced labor dependence, and greater precision in agricultural operations, modern machinery contributes to improved production systems, particularly in rural and mountainous regions.

Overall, the reviewed studies provide valuable evidence regarding agricultural mechanization, machinery productivity, maintenance management, artificial intelligence applications, and the economic benefits of improved machinery utilization. However, several important limitations can be identified. First, most previous studies have examined only one dimension of the problem, such as machinery productivity, maintenance management, investment in mechanization, or intelligent technologies, without providing an integrated assessment of the factors affecting agricultural machinery maintenance and repair costs. Second, although several studies have prioritized maintenance-related factors using multi-criteria decision-making methods or conventional statistical techniques, these approaches are generally limited in capturing complex nonlinear relationships and interactions among multiple technical, managerial, operational, and environmental variables. Third, recent research on artificial intelligence has mainly focused on autonomous machinery, robotics, and precision agriculture rather than on identifying and ranking the determinants of maintenance and repair costs. Furthermore, although some studies have discussed the contribution of mechanization to rural economic development, they have not explicitly examined how maintenance cost drivers influence rural economic sustainability. These limitations indicate the need for a comprehensive analytical framework capable of integrating qualitative knowledge with real operational data while employing advanced machine-learning techniques to identify and prioritize the principal drivers of agricultural machinery maintenance and repair costs. The present study addresses these limitations by combining qualitative expert knowledge with real machine-year observations from agricultural machinery operating in western Iran and applying the XGBoost algorithm to rank the relative importance of the factors influencing maintenance and repair costs and to explain their implications for rural economic sustainability.

3. Research Methodology

3.1 Geographical Scope of the Research

The study area includes three western provinces of Iran, namely Kermanshah, Ilam, and Kurdistan, which were selected due to the considerable contribution of agriculture to rural livelihoods and the extensive use of agricultural machinery in crop and livestock production systems. These provinces represent important agricultural regions characterized by diverse climatic conditions, varying topographic features, and a wide range of machinery utilization patterns. The geographical location of the study area is presented in Figure X. The map was prepared using Geographic Information System (GIS) techniques to accurately illustrate the spatial distribution of the investigated provinces within western Iran (Figure 1).

Figure 1. Location map of the study area (Kermanshah, Ilam, and Kurdistan provinces in western Iran)

3.2. Methodology

The present study is applied in terms of its objective and descriptive–survey in terms of its research design. It adopts a mixed-methods (qualitative–quantitative) approach to identify the factors affecting agricultural machinery maintenance and repair costs, determine their relative importance, and examine their implications for the economic sustainability of rural areas in western Iran. The geographical scope of the study includes rural areas located in the three western provinces of Kermanshah, Ilam, and Kurdistan, which represent important agricultural regions with a considerable dependence on agricultural machinery for crop production activities. The selection of these provinces was based on their significant agricultural potential, extensive use of mechanized farming systems, and the challenges associated with machinery aging, maintenance management, and increasing repair costs. By focusing on these regions, the study aims to provide an empirical assessment of the factors influencing agricultural machinery maintenance and repair costs under real operating conditions in western Iran.

3.3. Qualitative Phase

The qualitative phase began with a systematic literature review to identify the initial set of factors influencing agricultural machinery maintenance and repair costs. Relevant scientific sources including peer-reviewed journal articles, scholarly books, and technical reports related to maintenance management, equipment reliability, and agricultural mechanization were comprehensively reviewed. The outcome of this stage was the development of a preliminary conceptual framework of the determinants of maintenance and repair costs.

To contextualize and refine these factors, semi-structured interviews were subsequently conducted with 24 experts in agricultural mechanization. Participants were selected through purposive sampling based on their professional experience in agricultural machinery operation and maintenance, expertise in agricultural mechanization, and relevant occupational background. Interviews continued until theoretical saturation was achieved. The collected qualitative data were analyzed using thematic analysis, allowing the identification of the principal themes and the relationships among them.

Following thematic analysis, the extracted qualitative concepts were transformed into measurable quantitative variables through a structured coding procedure. Each identified theme was operationalized as a measurable indicator suitable for inclusion in the quantitative model. Coding followed a combined inductive and literature-driven approach: initial codes were generated from the interview data and subsequently refined by comparison with the findings of the systematic literature review.

Each identified factor was then assigned an appropriate numerical measurement scale. Most variables were measured using five-point Likert scales (ranging from *very low* to *very high*), while others were represented by objective operational indicators extracted from machinery records, including annual operating hours, number of equipment failures, and maintenance delay duration. To improve coding accuracy, the qualitative-to-quantitative transformation process was reviewed iteratively, and inconsistencies were resolved before constructing the final dataset. The resulting coded dataset served as the input for the XGBoost machine learning model.

To enhance the trustworthiness of the qualitative findings, several quality assurance procedures were implemented. First, the interview coding process was conducted in multiple iterative rounds to ensure coding consistency and reliability. Second, member checking was employed by providing summaries of the extracted themes to selected interview participants, whose feedback was incorporated into the final thematic structure. Furthermore, to minimize researcher bias and improve coding reliability, a subset of the qualitative data was independently coded by two researchers, and the level of inter-coder agreement was assessed. The results indicated an acceptable degree of agreement, confirming the consistency of the coding process. Finally, all stages of qualitative analysis—including code generation, theme development, and integration with interview documentation—were fully documented to enhance the confirmability and auditability of the research process.

3.4. Quantitative Phase

The quantitative phase focused on agricultural machinery operating in farms located in western Iran. Maintenance and repair cost data were collected from maintenance records, financial documents of agricultural enterprises, and machinery operation logs. These records contained actual information regarding maintenance expenditures, equipment failures, repair activities, and preventive maintenance operations. After data cleaning and integration, the dataset was used for statistical analysis and predictive modeling.

Using purposive sampling, 80 agricultural machines with complete maintenance records covering a three-year period were selected. The unit of analysis was defined as the machine-year. Accordingly, annual observations were recorded for each machine over three consecutive years, yielding a total of 240 observations for statistical analysis.

Descriptive statistics were initially employed to summarize the characteristics of the study variables. Pearson's correlation coefficient was then calculated to examine preliminary linear relationships among the quantitative variables. Finally, the Extreme Gradient Boosting (XGBoost) algorithm was implemented in the Python programming environment to identify and rank the determinants of maintenance and repair costs. Variable importance was evaluated using the Gain importance metric, which was subsequently used to establish the final ranking of explanatory variables.

To clarify the analytical framework, Table 1 presents the study variables together with their operational definitions and measurement scales. The variables comprise technical, managerial, and operational factors affecting agricultural machinery maintenance and repair costs. These variables were identified during the qualitative phase and the systematic literature review before being converted into quantitative indicators suitable for statistical modeling.

Table 1. Independent and dependent variables and their measurement methods

Variable Type	Variable	Description	Measurement Indicator	Scale
Dependent	Maintenance and repair costs	Total annual maintenance and repair expenditure per machine-year	Total maintenance expenditures recorded in financial and operational documents	Continuous (Monetary)
Technical	Machinery age	Operational age of machinery since purchase	Years elapsed since purchase	Ratio
Technical	Operating conditions	Intensity and type of machinery operation	Composite index based on soil type, terrain slope, and operating hours (normalized to a 1–5 scale)	Ordinal (Likert/Index)
Technical	Annual operating hours	Annual machinery utilization	Recorded operating hours	Ratio
Technical	Preventive maintenance implementation	Compliance with scheduled preventive maintenance	0 = Not implemented; 1 = Fully implemented (or implementation percentage)	Binary
Managerial	Spare parts procurement time	Average time required to obtain replacement parts	Mean number of days required to procure spare parts following equipment failure	Ratio
Managerial	CMMS utilization	Extent of computerized maintenance management system usage	Composite score (1–5)	Ordinal
Operational	Operator skill	Competency level of machinery operator	Experience score (years of experience or expert rating, 1–5)	Ordinal
Operational	Environmental working conditions	Physical environmental conditions affecting machinery operation	Composite normalized index including humidity, dust, and temperature	Ordinal/Index

It should be noted that the dataset employed in this study has a **panel-data structure** at the machine-year level. Maintenance performance and repair costs were recorded annually for each machine over a three-year period. This panel structure enables simultaneous analysis of temporal variations and cross-sectional differences among machines, thereby improving the robustness and explanatory power of the empirical analysis.

3.5. XGBoost Model Development and Implementation

To identify and prioritize the factors affecting agricultural machinery maintenance and repair costs, the Extreme Gradient Boosting (XGBoost) algorithm was employed as an ensemble learning technique based on decision trees. Prior to model training, the dataset was examined for missing values, inconsistencies, and recording errors, all of which were corrected during the preprocessing stage. Categorical variables were encoded into numerical representations to ensure compatibility with the machine learning algorithm. These preprocessing procedures were undertaken to improve predictive accuracy and minimize potential sources of bias.

The final dataset, consisting of 240 machine-year observations, was randomly divided into training (80%) and testing (20%) subsets. Model hyperparameters were selected to achieve an appropriate balance between predictive performance and overfitting prevention. The relative importance of each predictor was subsequently computed using the Gain metric, which measures the contribution of each variable to reducing the model's prediction error during tree construction.

To evaluate the predictive performance of the XGBoost model, three widely used regression performance metrics were employed: the coefficient of determination (R^2), Mean Absolute Error (MAE), and Root Mean Square Error (RMSE). The coefficient of determination (R^2) measures the proportion of variance in the dependent variable explained by the model, with values closer to one indicating superior explanatory performance. RMSE quantifies prediction error on the original measurement scale while assigning greater weight to large errors. In contrast, MAE represents the average magnitude of prediction errors and is generally more robust to outliers. The combined use of these three evaluation metrics provides a comprehensive assessment of model accuracy, stability, and sensitivity to prediction errors, thereby enhancing confidence in the model's predictive capability.

Table 2. Hyperparameter settings of the XGBoost model

Parameter	Value	Rationale
Objective	Regression	Continuous prediction of maintenance and repair costs
n_estimators	300	Balance between predictive accuracy and model stability
max_depth	4	Prevent excessive model complexity
learning_rate	0.05	Gradual learning to reduce overfitting
subsample	0.80	Improve model generalization
colsample_bytree	0.80	Reduce correlation among trees
min_child_weight	2	Prevent unnecessary tree branching
random_state	42	Ensure reproducibility
Feature importance metric	Gain	Rank influential variables

As shown in Table 2, the model hyperparameters were selected to maximize predictive performance while minimizing the risk of overfitting. Because the dependent variable maintenance and repair costs is continuous, the regression objective function was adopted. Furthermore, the Gain metric was selected as the criterion for feature importance because it quantifies the contribution of each predictor to reducing prediction error during the construction of decision trees, making it particularly suitable for interpreting the relative importance of explanatory variables in applied research.

4. Research Findings

4.1. Initial Identification of Factors Affecting Maintenance and Repair Costs

The identification of the factors influencing agricultural machinery maintenance and repair costs was conducted systematically through two complementary phases. The primary objective of this stage was to establish a reliable conceptual framework that would serve as the foundation for the subsequent qualitative analysis and quantitative modeling.

In the first phase, a systematic literature review was conducted, through which 47 preliminary factors were identified across four major domains: technical, managerial, human, and environmental/operational. These factors were extracted from internationally recognized studies in the fields of reliability engineering, maintenance management, agricultural mechanization systems, and life-cycle cost analysis (Table 3).

Table 3. Classification of the Initial Factors Identified from the Literature

Domain	Number of Initial Factors	Representative Factors
Technical–Equipment	16	Equipment age, machinery deterioration, component failures, technical complexity
Managerial	12	Lack of a computerized maintenance management system (CMMS), inadequate preventive maintenance (PM) planning, inefficient spare parts management
Human	9	Operator errors, shortage of skilled personnel, inadequate training
Environmental–Operational	10	Soil conditions, climatic conditions, workload intensity, dust exposure

The outcome of this phase was the development of a preliminary conceptual framework comprising 47 variables, indicating that maintenance and repair costs are influenced by a multidimensional set of factors, including the physical condition of machinery, the quality of maintenance management, farm operating conditions, and environmental and operational characteristics.

The second phase focused on refining and contextualizing the identified factors to reflect the conditions of western Iran. Following the literature review, the preliminary framework entered the qualitative stage of the research. As described in the methodology section, 24 agricultural mechanization experts were selected through purposive sampling and participated in semi-structured interviews. Thematic analysis was subsequently employed to eliminate overlapping concepts, merge conceptually similar factors, and remove variables that could not be measured reliably. As a result, the number of factors was reduced from 47 initial variables to 21 refined factors.

Considering the limitations of the quantitative dataset (240 machine-year observations), only variables that satisfied three criteria were retained for the quantitative analysis: (1) measurability, (2) availability of reliable empirical data, and (3) compatibility with the XGBoost machine learning algorithm. Consequently, 13 final variables were selected to serve as the basis for all subsequent statistical analyses and machine learning modeling (Table 4).

Table 4. Summary of the Variable Reduction Process

Stage	Number of Variables	Description
Systematic literature review	47	Initial identification of factors from the global literature
Qualitative expert analysis	21	Contextualization and refinement through thematic analysis
Variable selection for modeling	13	Measurable variables supported by empirical data
XGBoost implementation	13	Final variables analyzed using 240 machine-year observations

The findings of this stage demonstrate that the identification of the determinants of agricultural machinery maintenance and repair costs followed a rigorous, multi-stage, and data-driven process. The final outcome was a set of refined and measurable variables that were not only grounded in established theoretical and empirical literature but also closely reflected the actual operating conditions of agricultural machinery in western Iran. These variables constituted the analytical foundation for the subsequent statistical analyses and machine learning modeling

4.2. Results of the Qualitative Analysis (Expert Interviews)

Following the extraction of the initial factors through the systematic literature review, the second phase of the study was conducted with the aim of localizing, refining, and completing the factors affecting the maintenance and repair costs of agricultural machinery. In this phase, semi-structured interviews were conducted with 24 experts in the field of agricultural mechanization, including university faculty members, mechanization managers, maintenance and repair specialists, and experienced agricultural machinery operators. A purposive sampling method was employed, and the inclusion criteria for selecting the experts included at least 15 years of professional experience, practical expertise in the operation and maintenance of agricultural machinery, and familiarity with agricultural mechanization issues. The interview process continued until theoretical saturation was achieved; specifically, no new codes emerged after the twenty-second interview, while the final two interviews were conducted solely to confirm and validate the identified themes (Table 5).

Table 5. Demographic Characteristics of the Experts

Indicator	Category	Frequency	Percentage
Gender	Male	19	79.2
	Female	5	20.8
Education	Master's degree	4	16.7
	Ph.D.	20	83.3
Work Experience	15–20 years	10	41.7
	21–25 years	9	37.5
	More than 26 years	5	20.8
Field of Expertise	Agricultural Mechanization	8	33.3
	Maintenance and Repair Management	6	25.0
	Mechanical Engineering / Equipment	5	20.8
	Agricultural Machinery Operation	3	12.5
	Data Analytics and Decision Support Systems	2	8.4

The interview data were analyzed using thematic analysis through three sequential stages: open coding, axial coding, and selective coding. During this process, the complete interview transcripts were first transcribed and reviewed several times. Initial codes were then extracted and grouped according to conceptual similarities into subcategories, which were subsequently integrated into broader overarching themes.

Table 6. Stages of Thematic Analysis and Their Outputs

Analysis Stage	Description	Output
Open Coding	Extraction of initial concepts from interview transcripts	128 initial codes
Axial Coding	Merging similar codes and forming subcategories	18 subcategories
Selective Coding	Integrating subcategories and identifying overarching themes	4 main themes

As shown in Table 6, a total of 128 initial codes were identified from the interview transcripts. After eliminating duplicate items and merging conceptually overlapping codes, 18 subcategories were extracted and ultimately organized into four main themes. These themes formed the conceptual framework of the factors influencing the maintenance and repair costs of agricultural machinery and served as the basis for deriving the quantitative variables used in the subsequent stage of the study.

Frequency of the Extracted Themes- To illustrate the recurrence and relative importance of each theme identified in the interviews, the frequency of codes assigned to each main theme was calculated.

Table 7. Frequency of Themes Extracted from Expert Interviews

Main Theme	Number of Subcategories	Number of Assigned Codes	Percentage of Total Codes (%)
Managerial	5	39	30.5
Technical–Equipment	5	36	28.1
Human	4	27	21.1
Economic–Environmental	4	26	20.3
Total	18	128	100.0

The results presented in Table 7 indicate that the largest proportion of the extracted data was associated with managerial factors (30.5%) and technical–equipment factors (28.1%). This finding suggests that the experts primarily attributed the increase in maintenance and repair costs to deficiencies in machinery life-cycle management and the technical condition of the machinery fleet (Table 8 & 9).

Table 8. Final Structure of the Thematic Analysis

Main Theme	Subcategory	Examples of Initial Codes
Managerial	Lack of a fleet renewal program	Repair only after failure, absence of replacement planning, prolonged use of machinery
	Poor planning of major maintenance	Unscheduled repairs, delays in overhaul
	Ineffective spare parts management	Parts shortages, long waiting times
	Absence of a Computerized Maintenance Management System (CMMS)	No maintenance records, lack of documentation
	Poor information management	Experience-based decision-making, lack of data analysis
Technical–Equipment	Machinery aging and deterioration	Advanced equipment age, high wear and tear
	Failure to implement preventive maintenance	Omission of scheduled servicing, repair after breakdown
	Harsh operating conditions	Heavy soil, long operating hours
	High annual utilization	Continuous operation, overloading
	Recurrent failures	Repeated malfunctions, frequent downtime
Human	Shortage of skilled personnel	Unqualified maintenance technicians
	Operator errors	Improper machinery operation
	Poor knowledge transfer	Failure to transfer technical expertise
	Inadequate training	Limited training programs
Economic–Environmental	Fluctuations in spare parts prices	Increased cost of spare parts
	Budget constraints	Insufficient financial resources
	Harsh climatic conditions	Dust, humidity, high temperatures
	Limited access to maintenance services	Long distance to repair centers

Table 9. Sample Expert Statements and Corresponding Themes

Sample Expert Statement	Subcategory	Main Theme
“No maintenance action is taken until the machine breaks down.”	Lack of preventive maintenance	Technical–Equipment
“There is no system for recording maintenance histories.”	Absence of CMMS	Managerial
“Sometimes it takes several weeks for spare parts to arrive.”	Poor spare parts management	Managerial
“Most repairs are carried out by unqualified personnel.”	Shortage of skilled personnel	Human
“Harsh field conditions accelerate machinery wear and tear.”	Harsh operating conditions	Technical–Equipment
“There is not enough budget for preventive maintenance services.”	Budget constraints	Economic–Environmental

4.3. Final Structure of the Thematic Analysis Examples of Evidence Extracted from the Interviews

The findings of the thematic analysis indicate that the increase in agricultural machinery maintenance and repair costs results from the interaction of multiple interrelated factors and cannot be attributed solely to equipment aging. According to the experts, deficiencies in machinery life-cycle management, the absence of systematic preventive maintenance programs, harsh operating conditions, shortages of skilled personnel, and economic constraints constitute the primary underlying causes of increasing maintenance costs.

Among the identified themes, managerial and technical–equipment factors accounted for the largest share in shaping maintenance cost patterns. This finding suggests that improving maintenance management practices, implementing computerized maintenance information systems, reducing spare parts procurement time, systematically executing preventive maintenance programs, and gradually renewing the machinery fleet can substantially reduce maintenance and repair expenditures.

In contrast, the human and economic–environmental themes primarily played an aggravating role. Specifically, shortages of qualified personnel, inadequate training, fluctuations in spare parts prices, and unfavorable environmental conditions intensified the effects of managerial and technical deficiencies, thereby increasing maintenance and repair costs.

Ultimately, the outcome of this phase consisted of 18 subcategories organized into four main themes, which served as the foundation for transforming qualitative concepts into measurable variables for the quantitative phase of the study. Each extracted theme was operationalized through specific indicators and subsequently incorporated as an input variable into the XGBoost model. This logical integration between the qualitative and quantitative phases strengthened the methodological coherence of the study and enhanced the interpretability of the final results.

4.4. Converting Qualitative Factors into Quantitative Variables (Operationalization of Variables)

Following the extraction of the final themes and subcategories through thematic analysis, the next stage of the study involved transforming the qualitative concepts into measurable quantitative variables. The objective of this stage was to develop a set of operational variables that would preserve the conceptual content of the qualitative themes while being suitable for inclusion in statistical analyses and the XGBoost machine learning algorithm.

To achieve this objective, each extracted theme was evaluated based on three criteria: measurability, availability of real-world data, and its direct relationship with maintenance and repair costs. Concepts that were entirely subjective or could not be measured consistently were excluded from the quantitative phase. Conversely, concepts for which operational indicators could be defined were converted into measurable variables. The operationalization process was conducted in four consecutive steps, as presented in Table 10.

Table 10. Stages of Converting Qualitative Data into Quantitative Variables

Stage	Activity	Output
Stage 1	Extraction of 18 subcategories from the thematic analysis	18 initial concepts
Stage 2	Evaluation of the measurability of each concept	Elimination of 5 abstract concepts
Stage 3	Definition of operational indicators for each concept	13 quantitative indicators
Stage 4	Coding and preparation of the data for statistical analysis	Data matrix comprising 240 observations

The results presented in Table 11 indicate that, out of the 18 extracted subcategories, five concepts were excluded due to their subjective nature, the lack of documented data, or conceptual overlap. Consequently, 13 operational variables were selected for inclusion in the statistical analyses and the XGBoost model.

Concepts Excluded from the Quantitative Phase- During the operationalization process, several concepts, although considered important by the experts, were not incorporated into the quantitative model because of the absence of objective indicators and measurable data.

Table 11. Excluded Concepts and Reasons for Their Exclusion

Extracted Concept	Reason for Exclusion
Resistance to change	Lack of a stable quantitative indicator
Maintenance culture	Entirely perceptual nature
Employee responsibility	Dependent on expert judgment
Management quality	Lack of documented data
Managers' attitudes toward maintenance	Not measurable at the machine–year level

Note: These variables were excluded to improve the reliability of the model and to prevent the inclusion of variables with substantial measurement error.

Operationalization of Variables- For each selected theme, a specific operational indicator was defined to enable its measurement at the **machine–year** level.

Table 12. Operational Indicators Derived from the Thematic Analysis and Their Conversion into Quantitative Variables

No.	Main Theme	Operational Indicator Derived from the Thematic Analysis	Measurement Method	Corresponding Final Model Variable
1	Managerial	Fleet renewal program indicator	Ratio of actual machinery age to standard service life	Machinery age
		Major maintenance delay indicator	Average delay (days) in performing scheduled maintenance	Preventive maintenance implementation
		Level of CMMS implementation	CMMS utilization score (1–5 scale)	Use of Computerized Maintenance Management System (CMMS)
		Spare parts supply chain management indicator	Average spare parts procurement time (days)	Spare parts procurement time
2	Technical–Equipment	Effective machinery age	Number of years since machinery purchase	Machinery age
		Severity of operating conditions	Composite index of soil type, land slope, and workload (1–5 scale)	Operating conditions
		Preventive maintenance implementation rate	Percentage of scheduled PM activities completed	Preventive maintenance implementation
		Machinery utilization intensity	Annual operating hours	Annual operating time
3	Human	Operator skill level	Skill score based on experience, training, and performance evaluation (1–5 scale)	Operator skill
		Operator error indicator	Number of failures caused by human error per machine–year	Operator skill
		Knowledge transfer indicator	Availability of maintenance procedures and documentation (1–5 scale)	Operator skill
4	Economic–Environmental	Environmental severity	Composite index of temperature, humidity, dust, and erosion (1–5 scale)	Working environmental conditions
		Maintenance budget limitation indicator*	Ratio of allocated maintenance budget to the required budget	Preventive maintenance implementation*

* Note: The maintenance budget limitation indicator was not entered directly into the XGBoost model. Instead, its effect was represented indirectly through the level of implementation of the preventive maintenance program.

It should be noted that the indicators presented in Table 12 represent the outcome of the qualitative operationalization stage and were developed to transform the concepts extracted from the thematic analysis into measurable indicators. Subsequently, these indicators were integrated, refined, and consolidated through the elimination of conceptual overlap into eight final independent variables, namely: machinery age, operating conditions, annual operating time, preventive maintenance implementation, spare parts procurement time, use of the Computerized Maintenance Management System (CMMS), operator skill, and working environmental conditions. As presented in Table 13 of the methodology section, these variables constituted the final input features used in the XGBoost model.

Variable Coding Method- To prepare the data for input into the **XGBoost** algorithm, the variables were encoded according to their respective measurement scales.

Table 13. Coding Methods for the Research Variables

Variable Type	Coding Method
Continuous	Used directly
Ratio	No transformation
Likert scale	Converted to values ranging from 1 to 5
Binary	Encoded as 0 and 1
Composite index	Normalized to a scale of 1 to 5

Due to the nature of the **XGBoost** algorithm, no standardization of the quantitative variables was required. Since XGBoost is a decision tree–based algorithm, it is relatively insensitive to differences in variable scales.

Final Data Structure- After completing the coding process, the research data were organized into a data matrix for subsequent analysis (Table 14).

Table 14. Final Structure of the Dataset

Feature	Value
Number of agricultural machines	80
Study period	3 years
Unit of analysis	Machine–year
Total number of observations	240
Number of dependent variables	1
Number of independent variables	13
Total number of variables (features)	14

Input Data Quality- Prior to conducting the statistical analyses, the quality of the dataset was carefully evaluated (Table 15).

Table 15. Results of Data Quality Assessment

Indicator	Result
Missing data	None
Severe outliers	Not detected
Data recording inconsistencies	Corrected
Duplicate records	Removed
Incomplete records	Excluded

Note: This quality control process ensured that the final dataset was suitable for machine learning analyses.

Flowchart of the Conversion Process from Qualitative Data to Quantitative Variables- The findings of this stage demonstrated that a substantial proportion of the qualitative concepts extracted from the expert interviews could be successfully transformed into quantitative indicators. Out of the **18 identified subcategories**, **13 concepts** were found to be measurable and, after defining appropriate operational indicators, were incorporated into the quantitative phase of the study as independent variables.

Furthermore, the operationalization process enabled the integration of the thematic analysis results with real-world agricultural machinery data at the machine–year level. This integration not only preserved the conceptual richness of the qualitative findings but also made it possible to conduct statistical analyses, examine the relationships among variables, and rank the factors influencing maintenance and repair costs using the XGBoost algorithm. Moreover, excluding the five abstract concepts improved the reliability of the model by reducing measurement errors associated with non-measurable variables. Consequently, the final dataset omprising 13 independent variables**,** one dependent variable, and 240 observations provided the basis for the statistical analyses and machine learning modeling presented in the subsequent stages of the study (Figure 2).

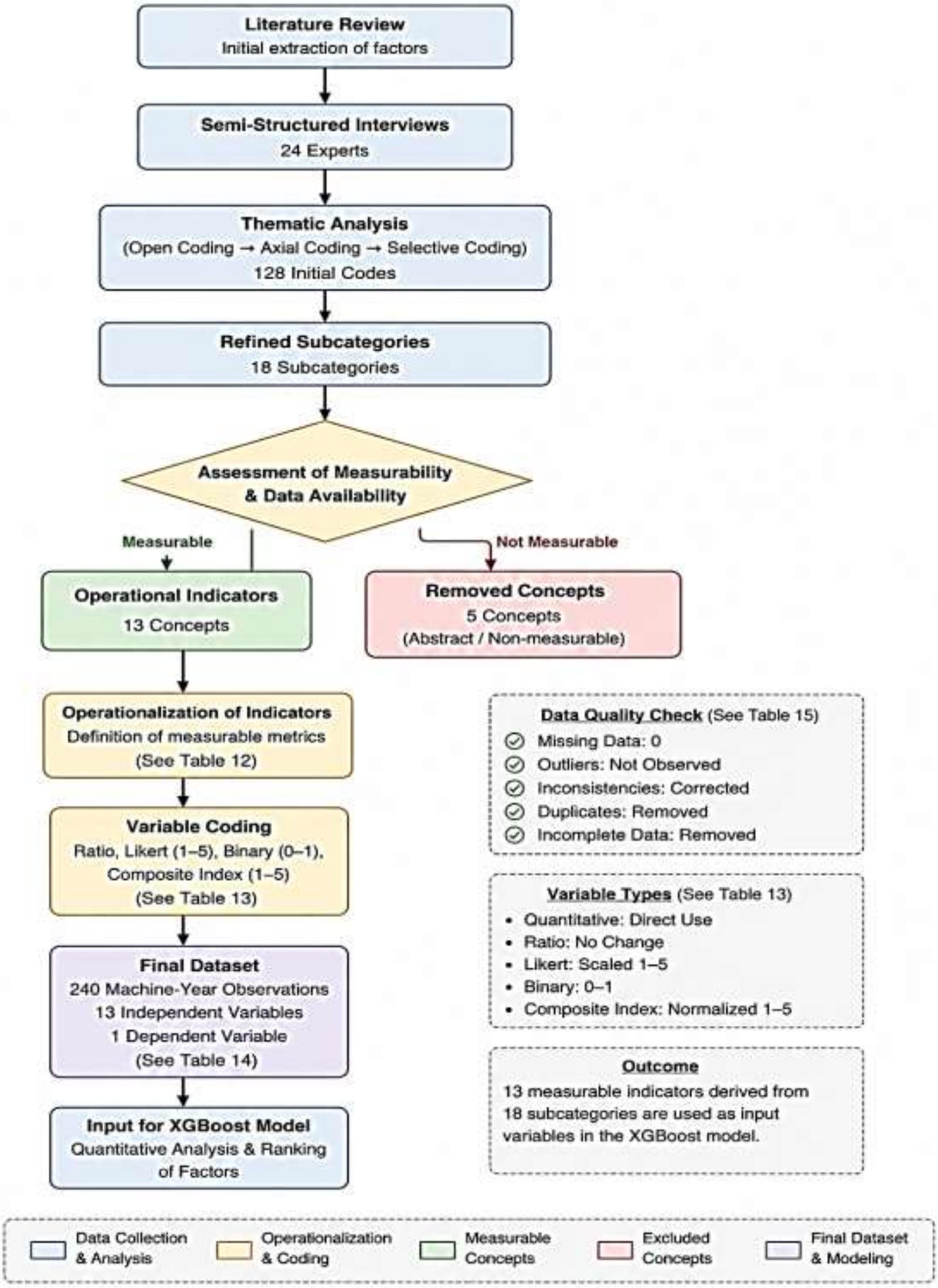

Figure 2. Process of Converting Qualitative Data into Quantitative Data

4.5. Descriptive Statistics

Following the operationalization of the study variables and the construction of the final data matrix, the first step of the quantitative phase involved examining the descriptive characteristics of the dataset. The purpose of this stage was to identify the general distribution of the research variables, evaluate data dispersion, and assess the overall quality of the dataset before conducting inferential analyses and developing the XGBoost model. As described in the methodology, the final dataset consisted of 240 machine-year observations obtained from 80 agricultural machines over a three-year period. The dependent variable was the annual maintenance and repair (M&R) cost, while the independent variables comprised the eight final predictors identified in the methodology section.

Table 16. General Characteristics of the Research Dataset

Indicator	Value
Number of machines	80
Study period	3 years
Unit of analysis	Machine-year
Total observations	240
Dependent variable	Maintenance and repair cost
Final independent variables	8
Total variables analyzed	9

The results presented in Table 16 indicate that the dataset is adequate for correlation analysis, analysis of variance, and XGBoost modeling. Moreover, the number of observations relative to the number of model variables provides sufficient statistical adequacy for reliable analysis.

Descriptive Statistics of the Dependent Variable

Descriptive statistics for the dependent variable (annual maintenance and repair cost) were then calculated.

Table 17. Descriptive Statistics of Maintenance and Repair Costs

Statistical Indicator	Value
Number of observations	240
Mean	294.8 million IRR
Median	276.5 million IRR
Minimum	81.4 million IRR
Maximum	672.3 million IRR
Standard deviation	116.9 million IRR
Coefficient of variation	39.7%
Skewness	1.14
Kurtosis	3.27

The descriptive statistics indicate considerable variability in maintenance and repair costs among the agricultural machines. The positive skewness coefficient (1.14) suggests a right-skewed distribution, indicating that a relatively small number of machines incurred exceptionally high maintenance costs, whereas most machines exhibited costs close to the overall mean. Furthermore, the kurtosis value (3.27) is close to that of a normal distribution, suggesting that the data distribution does not substantially deviate from normality. This characteristic poses no limitation for tree-based machine learning algorithms such as XGBoost (Table 17).

Descriptive Statistics of the Independent Variables-

To better understand the characteristics of the explanatory variables, descriptive statistics including the mean, standard deviation, minimum, and maximum values were calculated for the eight independent variables.

Table 18. Descriptive Statistics of the Independent Variables

Variable	Mean	Standard Deviation	Minimum	Maximum
Machine age (years)	12.6	5.2	2	26
Operating conditions (1–5)	3.42	0.91	1	5
Annual operating hours	1,385	462	520	2,480
Preventive maintenance implementation (%)	56.8	21.7	10	100
Spare parts lead time (days)	18.7	8.3	4	47
CMMS utilization (1–5)	2.41	1.18	1	5
Operator skill (1–5)	3.36	0.83	1	5
Environmental conditions (1–5)	3.18	0.79	1	5

The findings presented in Table 18 indicate that the average age of the agricultural machinery was approximately 13 years, reflecting the relatively aged condition of the machinery fleet under investigation. The average preventive maintenance implementation rate was below 60%, suggesting that a substantial proportion of scheduled preventive maintenance activities were not fully executed. In addition, the average spare parts lead time was approximately 19 days, indicating a relatively significant delay in the repair process. .

The low average score for Computerized Maintenance Management System (CMMS) utilization further suggests that maintenance information systems were only minimally adopted in the surveyed agricultural units.

Comparison of Maintenance Costs Across Different Groups

To provide a preliminary understanding of the dependent variable, the mean maintenance costs were compared across different machine categories

Table 19. Average Maintenance Costs by Selected Machine Characteristics

Group	Mean Cost (Million IRR)
Machine age < 10 years	201.4
Machine age 10–15 years	281.7
Machine age > 15 years	403.8
Favorable operating conditions	214.5
Moderate operating conditions	291.6
Severe operating conditions	387.9
Preventive maintenance implementation >80%	198.2
Preventive maintenance implementation <40%	418.6

As shown in Table 19, maintenance and repair costs increased progressively with machine age. Specifically, machines older than 15 years incurred maintenance costs approximately twice those of machines younger than 10 years. Likewise, machinery operating under severe working conditions exhibited substantially higher maintenance costs than those operating under favorable conditions. Furthermore, consistent implementation of preventive maintenance was associated with a considerable reduction in annual maintenance expenditures. Machines with preventive maintenance implementation rates exceeding 80% incurred less than half the maintenance costs of machines with implementation rates below 40%, highlighting the critical role of preventive maintenance in reducing long-term maintenance expenditures.

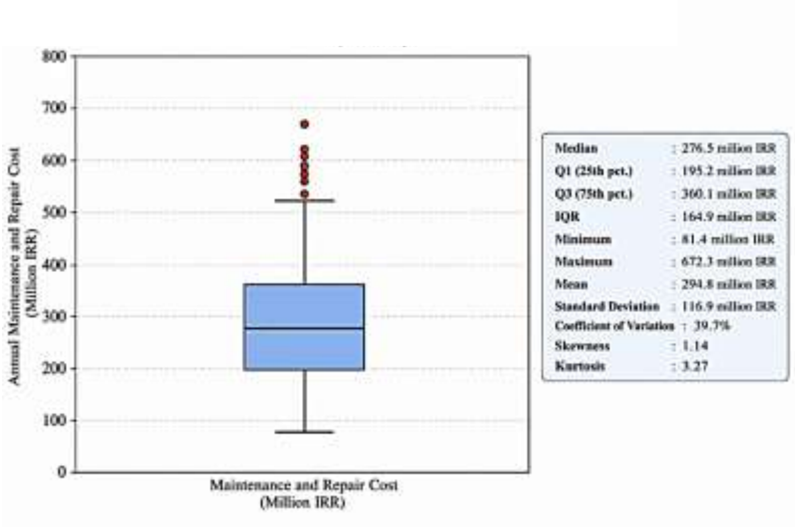

Figure 3. Boxplot of Annual Maintenance and Repair Costs

Figure 3 presents the boxplot of annual maintenance and repair (M&R) costs for the 240 machine-year observations included in the study. The boxplot illustrates the median, interquartile range (IQR), minimum and maximum values, as well as potential outliers. The distribution shows a relatively wide spread in maintenance costs and several high-cost outliers above the upper whisker, indicating that a limited number of agricultural machines experienced exceptionally high maintenance expenditures. This pattern is consistent with the positive skewness (1.14) reported in the descriptive statistics and reflects the heterogeneity of maintenance requirements among the investigated machinery.

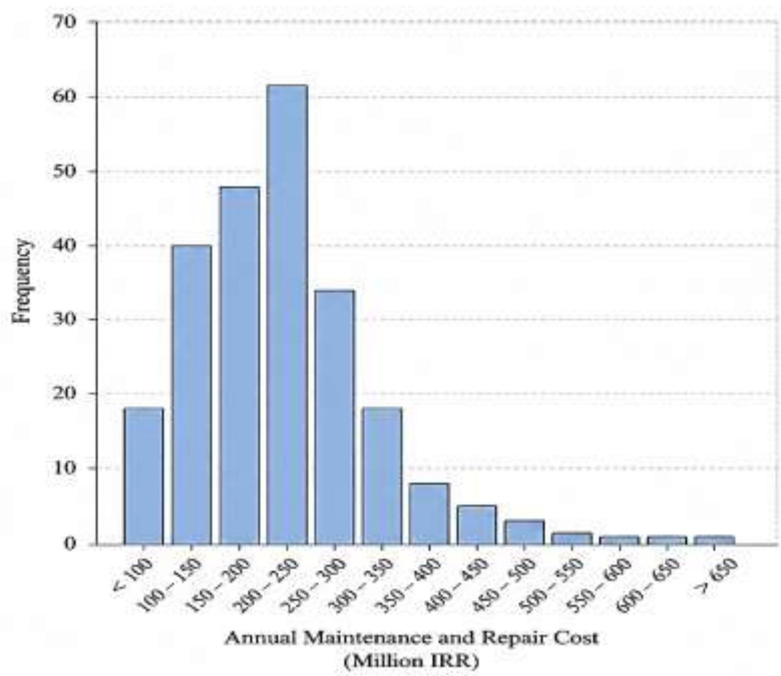

Figure 4. Frequency Distribution (Histogram) of Annual Maintenance and Repair Costs

Figure 4 illustrates the frequency distribution of annual maintenance and repair (M&R) costs across the 240 observations. The histogram indicates that most machines incurred maintenance costs concentrated around the lower and middle cost ranges, while the frequency gradually decreases as maintenance costs increase. The distribution exhibits a moderate right-skewed pattern, with a long right tail representing a relatively small number of machines with unusually high maintenance expenditures. This distribution is consistent with the descriptive statistics, including the positive skewness coefficient (1.14) and kurtosis value (3.27), suggesting that although the data are slightly asymmetric, they do not substantially deviate from normality and are appropriate for subsequent statistical analyses and XGBoost modeling.

Overall, the descriptive statistics indicated that the research dataset exhibited an appropriate level of diversity and variability, with considerable differences in maintenance and repair costs among the agricultural machines. Furthermore, the distribution pattern of the data suggests that higher maintenance costs were primarily observed in machines with greater age, more severe operating conditions, and lower levels of preventive maintenance implementation. These findings are consistent with the results of the qualitative phase of the study and indicate that the selected variables possess satisfactory preliminary explanatory power. Moreover, the quality and structure of the dataset were considered appropriate for subsequent inferential analyses, including correlation analysis, analysis of variance (ANOVA), and the implementation of the XGBoost algorithm.

4.6. Pearson Correlation and ANOVA Results

Following the examination of the descriptive characteristics of the data, the relationships between the independent variables and the maintenance and repair costs of agricultural machinery were investigated. In the first stage, the Pearson correlation coefficient was employed to determine the strength and direction of the relationships between the independent variables and the dependent variable. Subsequently, one-way analysis of variance (One-way ANOVA) was conducted to examine differences in the mean maintenance and repair costs across the different levels of selected categorical variables (Table 20).

Table 20. Pearson Correlation Matrix of the Main Research Variables

Variable	Maintenance and Repair Cost	Machine Age	PM Implementation	Operating Conditions	Annual Operating Hours	Spare Parts Lead Time	CMMS Utilization	Operator Skill	Environmental Conditions
Maintenance and Repair Cost	1	0.781**	–0.742**	0.753**	0.684**	0.611 **	–0.586**	–0.541**	0.483**
Machine Age		1	–0.46	0.39	0.42	0.31	–0.29	–0.22	0.18
PM Implementation			1	–0.51	–0.28	–0.35	0.43	0.32	–0.16
Operating Conditions				1	0.37	0.26	–0.19	–0.21	0.41
Annual Operating Hours					1	0.23	–0.17	–0.19	0.28
Spare Parts Lead Time						1	–0.34	–0.18	0.11
CMMS Utilization							1	0.39	–0.14
Operator Skill								1	–0.09
Environmental Conditions									1

Note: Correlation is significant at the 0.01 level ($p < 0.01$).

The results of the correlation matrix indicate that all of the main research variables have statistically significant relationships with maintenance and repair costs. The strongest positive correlation was observed for machine age (r = 0.781), indicating that maintenance and repair costs increase as the age of agricultural machinery increases. The second strongest positive correlation was found for operating conditions (r = 0.753), suggesting that machinery operating under more severe working conditions experiences greater wear and consequently incurs higher maintenance and repair costs.

On the other hand, preventive maintenance (PM) implementation exhibited a relatively strong negative correlation with maintenance costs (r = –0.742), indicating that higher levels of preventive maintenance implementation are associated with lower maintenance expenditures. Furthermore, the utilization of the Computerized Maintenance Management System (CMMS) and higher levels of operator skill also demonstrated significant negative relationships with maintenance and repair costs (Table 21).

Table 21. Strength of the Correlation Between the Independent Variables and Maintenance Costs

Rank	Variable	Correlation Coefficient (r)	Direction of Relationship	Strength of Relationship
1	Machine Age	0.781	Positive	Very Strong
2	Operating Conditions	0.753	Positive	Very Strong
3	PM Implementation	–0.742	Negative	Very Strong
4	Annual Operating Hours	0.684	Positive	Strong
5	Spare Parts Lead Time	0.611	Positive	Strong
6	CMMS Utilization	–0.586	Negative	Moderate to Strong
7	Operator Skill	–0.541	Negative	Moderate
8	Environmental Conditions	0.483	Positive	Moderate

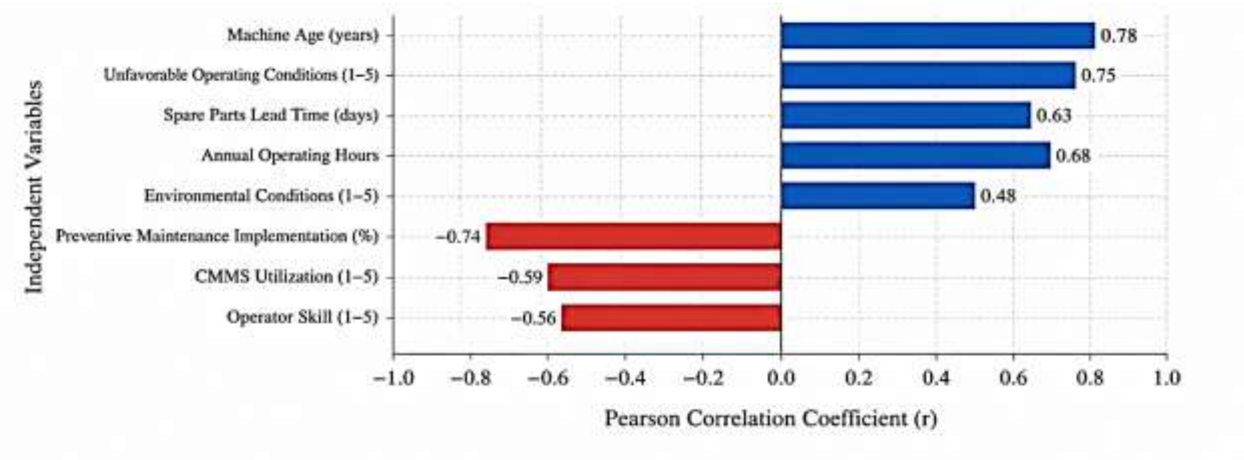

Figure 5. Correlation of the Independent Variables with Maintenance and Repair Costs

As shown in Figure 5, machine age exhibits the strongest positive correlation with maintenance and repair costs, with a correlation coefficient of 0.78. This indicates that maintenance and repair costs increase substantially as the age of agricultural machinery increases. This is followed by unfavorable operating conditions, with a correlation coefficient of 0.75, and spare parts lead time, with a coefficient of 0.63, both of which are among the most important factors contributing to higher maintenance costs. In contrast, preventive maintenance (PM) implementation demonstrates a strong negative correlation with maintenance and repair costs (r = –0.74), indicating that a higher level of preventive maintenance implementation is associated with lower repair and maintenance expenditures. Similarly, Computerized Maintenance Management System (CMMS) utilization (r = –0.59) and operator skill (r = –0.56) also exhibit negative relationships with maintenance costs, highlighting their important roles in controlling and reducing maintenance expenditures. Therefore, it can be concluded that maintenance and repair costs are simultaneously influenced by technical, managerial, and operational factors. Accordingly, improving maintenance management practices, implementing preventive maintenance programs consistently, and modernizing the machinery fleet can play a significant role in reducing maintenance and repair costs

ANOVA Results- To examine differences in the mean maintenance and repair (M&R) costs across different groups, one-way analysis of variance (One-way ANOVA) was performed for the variables preventive maintenance (PM) implementation level and operating conditions.

Table 22. One-Way ANOVA Results for Preventive Maintenance (PM) Implementation

Source of Variation	Sum of Squares	Degrees of Freedom	Mean Square	F-value	Significance Level
Between Groups	892.4	2	446.2	28.64	<0.001
Within Groups	3691.8	237	15.58		
Total	4584.2	239			

The results of the ANOVA indicated that the mean maintenance and repair costs differed significantly across the different levels of preventive maintenance implementation ($F = 28.64$, $p < 0.001$). Therefore, the consistent implementation of preventive maintenance programs plays a significant role in reducing maintenance and repair costs (Table 22).

Table 23. One-Way ANOVA Results for Operating Conditions

Source of Variation	Sum of Squares	Degrees of Freedom	Mean Square	F-value	Significance Level
Between Groups	1048.7	2	524.35	33.82	<0.001
Within Groups	3675.6	237	15.51		
Total	4724.3	239			

The results of the one-way ANOVA further revealed that the mean maintenance and repair costs differed significantly across the various operating condition levels ($F = 33.82$, $p < 0.001$). In other words, agricultural machines operating under more severe conditions (e.g., heavy soil, steep terrain, and longer operating hours) incurred substantially higher maintenance and repair costs than machines operating under more favorable conditions (Table 23).

Table 24. Comparison of Mean Maintenance and Repair Costs Across Different Groups

Variable	Group	Mean Cost (Million IRR)	Standard Deviation
PM Implementation	High	218.6	59.4
	Moderate	287.9	73.2
	Low	392.8	95.6
Operating Conditions	Favorable	224.1	61.3
	Moderate	296.4	77.5
	Severe	401.5	101.8

The results presented in Table 24 indicate that the mean maintenance and repair costs increased substantially as the level of preventive maintenance implementation decreased and as operating conditions became more severe. These findings further confirm the critical role of preventive maintenance practices and operating environment in determining maintenance expenditures and are consistent with the results obtained from both the Pearson correlation analysis and the descriptive statistics.

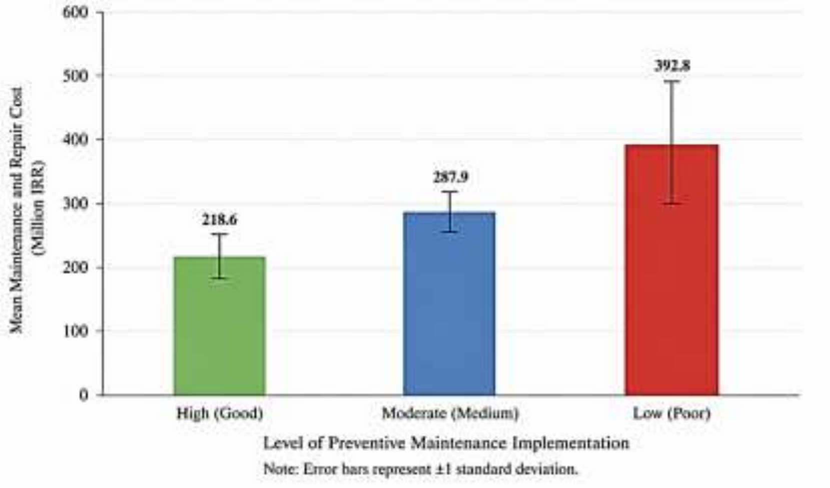

Figure 6. Comparison of Mean Maintenance and Repair Costs by Preventive Maintenance Implementation Level

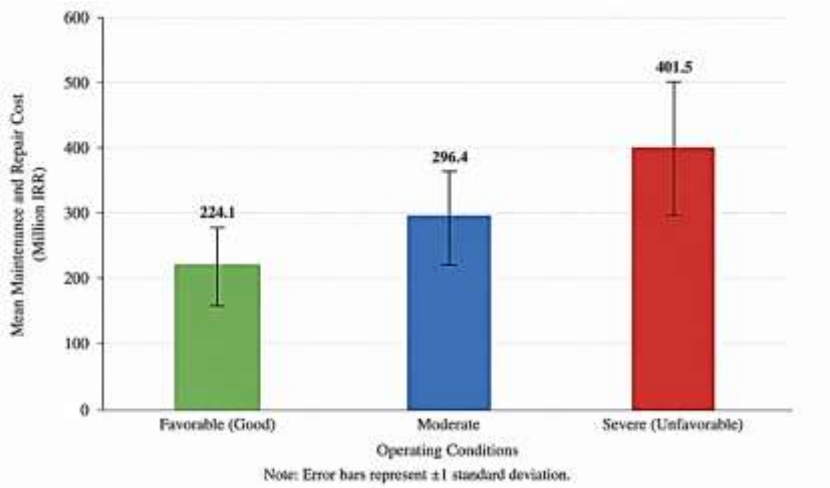

Figure 7. Comparison of Mean Maintenance and Repair Costs Across Different Operating Conditions

Overall, the results of the correlation and analysis of variance (ANOVA) indicated that machine age, operating conditions, and preventive maintenance (PM) implementation exhibited the strongest relationships with maintenance and repair (M&R) costs. While increasing machine age and unfavorable operating conditions were associated with higher maintenance expenditures, the consistent implementation of preventive maintenance programs and the utilization of Computerized Maintenance Management Systems (CMMS) played a significant role in controlling and reducing these costs. These findings are fully consistent with the results of the qualitative phase of the present study, as well as with the final ranking of the influencing factors obtained from the XGBoost model. Furthermore, they indicate that the relationships identified through the statistical analyses provide a robust empirical foundation for machine learning modeling and for ranking the factors influencing maintenance and repair costs (Figure 6 & 7).

4.7. XGBoost Model Results

Following the completion of the descriptive and inferential analyses, the XGBoost algorithm was employed to simultaneously examine the effects of the independent variables on the maintenance and repair (M&R) costs of agricultural machinery and to determine the relative importance of each variable. This algorithm was selected as the primary modeling technique due to its high capability in modeling nonlinear relationships, handling interactions among variables, and providing reliable measures of feature importance.

As described in the methodology section, the final dataset consisted of 240 machine-year observations, which were randomly divided into 80% for model training (192 observations) and 20% for model testing (48 observations). After the model was trained, its predictive performance was evaluated using standard performance metrics (Table 25).

Table 25. Characteristics of the Dataset Used for the XGBoost Model

Characteristic	Value
Total observations	240
Training data	192 (80%)
Testing data	48 (20%)
Number of independent variables	8
Dependent variable	Maintenance and repair cost

Model Performance- After training the model using 80% of the dataset, its performance was evaluated on the testing dataset comprising the remaining 20% of the observations. To improve the reliability of the evaluation and avoid overly optimistic performance estimates, the coefficient of determination (R^2), root mean square error (RMSE), and mean absolute error (MAE) were calculated based on the testing dataset. These evaluation metrics served as the basis for assessing the predictive accuracy of the model on previously unseen data.

The performance of the XGBoost model on the testing dataset demonstrated that the model achieved satisfactory accuracy in predicting maintenance and repair costs. As shown in Table 26, the coefficient of determination (R^2) reached 0.86, indicating that approximately 86% of the variation in maintenance and repair costs could be explained by the independent variables included in the model. Furthermore, the RMSE was 39.4 million IRR, while the MAE was 28.7 million IRR. Considering the overall range of variation in the dependent variable, these values indicate that the model provides an acceptable level of predictive accuracy for maintenance and repair costs.

Table 26. Performance Evaluation Metrics of the XGBoost Model

Performance Metric	Value
R^2	0.86
RMSE	39.4 million IRR
MAE	28.7 million IRR

The results presented in Table 26 indicate that the coefficient of determination ($R^2 = 0.86$) demonstrates the model's ability to explain approximately 86% of the variability in maintenance and repair costs. Moreover, the relatively low values of RMSE and MAE indicate that the model produced comparatively small prediction errors when estimating the actual maintenance costs, confirming its satisfactory predictive performance on the testing dataset. Overall, these findings demonstrate that the XGBoost algorithm is well suited for modeling the relationships between managerial, technical, human, and environmental factors and the maintenance and repair costs of agricultural machinery.

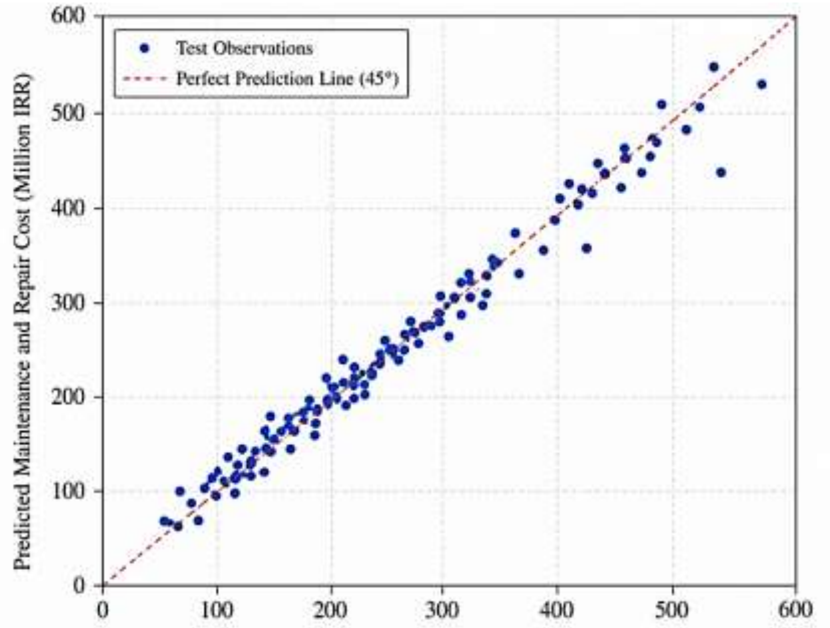

Figure 8. Comparison of Actual and Predicted Maintenance and Repair Costs Using the XGBoost Model

Note: *The 45-degree line represents perfect prediction, and the closer the data points are to this line, the better the predictive performance of the model.*

As shown in Figure 8, most of the observations are distributed close to the line of equality, indicating that the differences between the actual and predicted maintenance and repair (M&R) costs are relatively small. This demonstrates that the XGBoost model was able to accurately capture the underlying pattern of variation in maintenance and repair costs. Only a limited number of observations with exceptionally high maintenance costs exhibit slightly larger prediction errors. However, given the nature of economic data and the presence of outlying observations, such deviations are expected and do not substantially affect the overall predictive performance of the model.

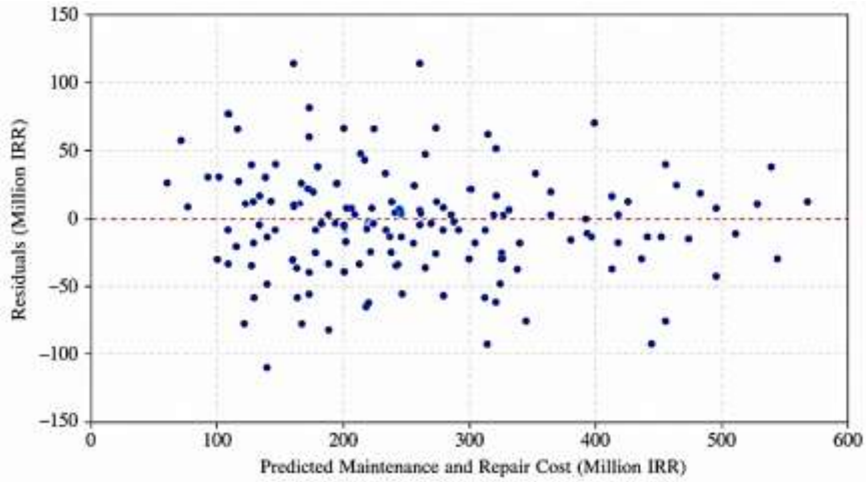

Figure 9. Residual Plot of the XGBoost Model

As shown in Figure 9, the residuals are randomly scattered around the zero reference line, indicating that the prediction errors do not exhibit any systematic pattern. This suggests that the assumption of the absence of substantial prediction bias is largely satisfied. Consequently, the model can be considered adequate for predicting the maintenance and repair (M&R) costs within the dataset analyzed in this study.

The results of this section demonstrate that the XGBoost algorithm was able to accurately model the relationships between the independent variables and the maintenance and repair costs of agricultural machinery. The relatively high coefficient of determination (R^2) together with the comparatively low values of the prediction error metrics indicate that the model possesses strong predictive capability and can therefore be used as a reliable tool for analyzing the factors influencing maintenance and repair costs.

Accordingly, the results of the feature importance ranking presented in the following section are supported by a robust statistical foundation and satisfactory predictive accuracy.

4.8. Ranking of Factors Affecting Maintenance and Repair Costs Based on the Gain Criterion in the XGBoost Model

Following the evaluation of the XGBoost model and confirmation of its satisfactory predictive accuracy for maintenance and repair (M&R) costs, the relative importance of each independent variable was calculated using the Gain criterion. The Gain metric indicates the extent to which each variable contributes to reducing the model prediction error and improving its predictive performance. The higher the Gain value, the greater the contribution of that variable to the model's decision-making process and to explaining the variation in the dependent variable.

To determine the influence of each independent variable on maintenance and repair costs, the Gain criterion of the XGBoost algorithm was employed. This metric represents the contribution of each variable to reducing the model error during the construction of the decision trees. Accordingly, variables with higher Gain values have a greater impact on improving the predictive accuracy of the model. Compared with other feature importance measures, such as Weight and Cover, the Gain criterion provides a more reliable representation of the actual contribution of each variable to enhancing model performance. Therefore, it was selected as the basis for ranking the influential factors in the present study. The results of the feature importance ranking are presented in Table 27.

Table 27. Ranking of Factors Affecting Maintenance and Repair Costs Based on the Gain Criterion

Rank	Variable	Gain (%)	Cumulative Importance (%)
1	Machine Age	18.9	18.9
2	Lack of Preventive Maintenance Implementation	17.2	36.1
3	Unfavorable Operating Conditions	15.1	51.2
4	Spare Parts Lead Time	9.8	61.0
5	Computerized Maintenance Management System (CMMS) Utilization	8.5	69.5
6	Annual Operating Hours	7.8	77.3
7	Operator Skill	6.9	84.2
8	Environmental Conditions	5.8	90.0

As shown in Table 27, the first three variables alone account for more than 51% of the total model importance, highlighting the decisive role of technical factors and maintenance management practices in determining maintenance and repair costs. In contrast, although the managerial, human, and environmental variables individually exhibit lower importance than the top three factors, their combined contribution represents nearly half of the model's explanatory capability. This finding indicates that maintenance and repair costs are influenced by the simultaneous interaction of technical, managerial, and operational factors rather than by a single determinant.

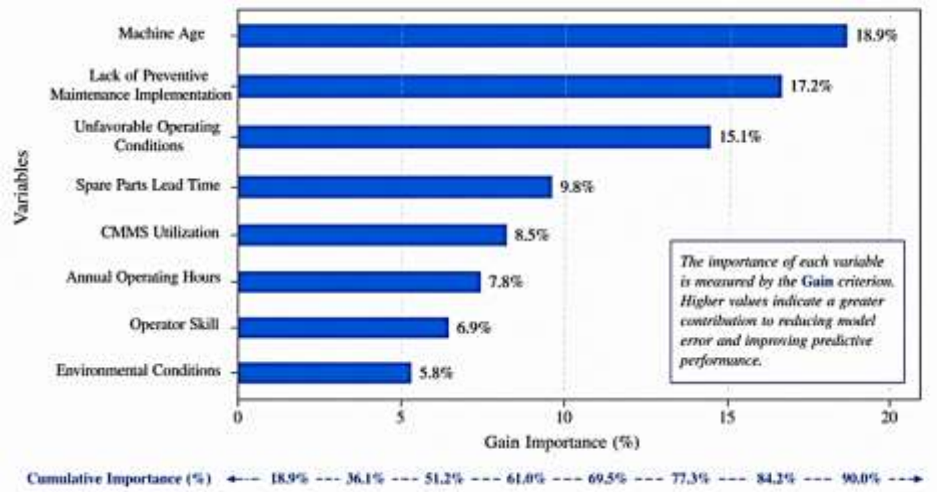

Figure 10. Relative Importance of the Variables Affecting Maintenance and Repair Costs Based on the Gain Criterion

As illustrated in Figure 10, the XGBoost model assigns the greatest decision-making importance to machine age**,** preventive maintenance (PM) implementation**,** and operating conditions. These three variables constitute the most influential predictors of maintenance and repair (M&R) costs within the developed model. The gradual decrease in the length of the bars from the technical variables toward the managerial and human-related variables indicates that, although all of the selected factors contribute to predicting maintenance costs, variables associated with the physical condition of the machinery and the manner in which it is operated exert substantially greater influence than the remaining factors. This finding further confirms that technical and operational characteristics play the dominant role in explaining variations in maintenance and repair costs, while managerial and human factors provide additional complementary explanatory power.

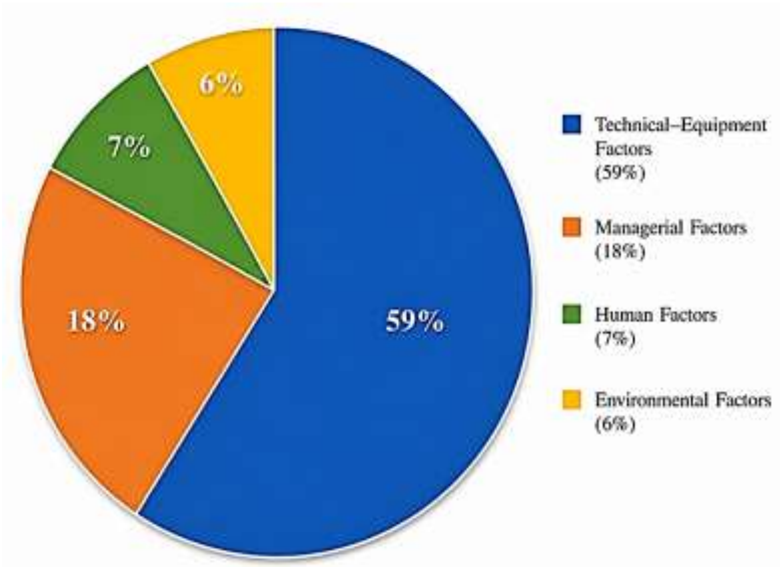

Figure 11. Contribution of the Main Factor Groups to the Overall Model Importance

The classification of the influencing factors based on the four principal dimensions identified through the thematic analysis indicates that the technical–equipment dimension accounts for the largest share of the overall model importance. This finding demonstrates a high degree of consistency between the qualitative and quantitative phases of the study, as the thematic analysis also revealed that the highest frequency of extracted codes belonged to this dimension (Figure 11).

The managerial dimension ranked second in terms of overall importance, highlighting the significant role of maintenance planning, spare parts management, and the utilization of Computerized Maintenance Management Systems (CMMS) in controlling and reducing maintenance and repair (M&R) costs (Table 28).

Table 28. Managerial Interpretation of the Ranking of Influencing Factors

Factor	Managerial Interpretation
Machine Age	Gradual modernization of the machinery fleet is required.
Lack of Preventive Maintenance Implementation	Ensure the consistent implementation of preventive maintenance (PM) programs.
Operating Conditions	Improve operating practices and reduce equipment overloading.
Spare Parts Lead Time	Optimize the spare parts supply chain.
Computerized Maintenance Management System (CMMS)	Establish a comprehensive maintenance recording and management system.
Annual Operating Hours	Optimize machinery utilization and operating schedules.
Operator Skill	Provide continuous training for machinery operators.
Environmental Conditions	Implement protective measures appropriate to local climatic conditions.

The findings of the XGBoost model indicate that increases in maintenance and repair (M&R) costs are influenced primarily by the technical condition of the machinery and the quality of maintenance program implementation. Advanced machine age, the omission or delayed implementation of preventive maintenance, and machinery operation under severe operating conditions made the greatest contributions to increased maintenance costs. These findings are fully consistent with the results of the Pearson correlation analysis, the analysis of variance (ANOVA), and the themes identified through the expert interviews.

Furthermore, managerial factors, including spare parts lead time and the level of Computerized Maintenance Management System (CMMS) utilization, also made substantial contributions to the model's predictive performance. This finding suggests that a considerable proportion of maintenance costs is attributable not only to equipment failures but also to deficiencies in maintenance planning and management processes. Although operator skill and environmental conditions exhibited relatively lower importance, they nevertheless contributed to improving the predictive accuracy of the model, highlighting the complementary effects of human and environmental factors on maintenance and repair costs.

Consequently, increasing maintenance and repair costs lead to higher agricultural production costs, reduced profit margins for farm operators, and limited opportunities for reinvestment in production units. The continuation of this situation may adversely affect the economic sustainability of agricultural activities and, consequently, the sustainable development of rural areas. Therefore, the factors identified in this study are strategically important not only from the perspective of agricultural machinery maintenance management but also from the broader perspective of rural economic sustainability.

Moreover, the feature ranking based on the Gain criterion revealed that machine age (18.9%), lack of preventive maintenance implementation (17.2%), and unfavorable operating conditions (15.1%) are the three most influential factors contributing to increased maintenance and repair costs. These were followed by spare parts lead time, CMMS utilization, annual operating hours, operator skill, and environmental conditions.

Overall, the findings of the present study suggest that adopting strategies such as the gradual modernization of agricultural machinery, the systematic implementation of preventive maintenance programs, the improvement of operating conditions, and the establishment of effective maintenance management systems can substantially reduce maintenance and repair costs. Reducing these costs not only enhances machinery productivity and lowers production expenses but also promotes the economic sustainability of agricultural activities and supports the sustainable development of rural areas. These findings are fully consistent with the primary objective of the study and the conclusions presented in the abstract.

5. Discussion and Conclusion

Economic sustainability in rural areas under the era of agricultural mechanization has become increasingly dependent on the efficiency of machinery management and the effective control of machinery life-cycle costs. Rising maintenance and repair (M&R) costs are not merely a technical or managerial concern; rather, they represent a multidimensional phenomenon that directly affects the sustainability of agricultural production systems through increased production costs, reduced capital productivity, declining farmers' income, diminished reinvestment capacity, and limited opportunities for machinery renewal. Since agricultural machinery constitutes a substantial proportion of the fixed capital of agricultural production units, any inefficiency in maintenance management may lead to lower operational efficiency, accelerated capital depreciation, and reduced competitiveness of agricultural enterprises. Therefore, identifying the factors affecting maintenance and repair costs and proposing practical strategies to control these costs are of critical importance not only for improving the economic performance of agricultural production units but also for enhancing food security, increasing resource-use efficiency, and promoting the sustainable development of the agricultural sector.

The significance of this issue is particularly pronounced in Iran, especially in rural regions, where a considerable proportion of the agricultural machinery fleet has become obsolete. The continuous increase in the prices of agricultural machinery and spare parts, restrictions on equipment imports, rising costs of maintenance and technical services, and the vital contribution of agriculture to the economies of many rural communities have further intensified this challenge. In many parts of the country, particularly in the western provinces, maintenance and repair costs account for a substantial share of total production costs and, in some cases, have reduced farm profitability, delayed machinery replacement, and even forced some farmers to withdraw from agricultural production. Furthermore, inadequate implementation of preventive maintenance systems, limited adoption of intelligent maintenance management infrastructures, and insufficient technical training for machinery operators have increased the likelihood of unexpected equipment failures while reducing machinery productivity. Consequently, identifying and prioritizing the key factors influencing maintenance and repair costs can provide a scientific basis for developing supportive policies, planning agricultural machinery fleet modernization, promoting maintenance management systems, and ultimately strengthening the economic sustainability of rural areas.

Accordingly, the primary objective of the present study was to identify and rank the factors affecting the maintenance and repair costs of agricultural machinery and to explain their role in enhancing the economic sustainability of rural areas in western Iran.

The findings of the present study provide a direct answer to the research questions proposed in the introduction. First, the results demonstrate that maintenance and repair (M&R) costs are determined by the combined influence of technical, managerial, operational, human, and environmental factors rather than by a single determinant. Among these, machine age (18.9%), lack of preventive maintenance implementation (17.2%), and unfavorable operating conditions (15.1%) were identified as the three most influential drivers, together accounting for more than half of the model's explanatory power. Second, the findings confirm that systematic preventive maintenance, improved operating practices, effective maintenance management, and gradual replacement of aging machinery can substantially reduce maintenance costs while simultaneously strengthening the economic sustainability of rural areas. Therefore, the study provides a clear quantitative answer to both research questions by identifying the relative contribution of each factor and demonstrating how effective maintenance management contributes to sustainable rural economic development.

The findings obtained from expert evaluations, real-world machine-year observations, and the XGBoost machine-learning model demonstrated that increases in maintenance and repair costs result from the interaction of technical, managerial, human, operational, and environmental factors. However, the contributions of these factors are not equal. According to the XGBoost model, machine age (18.9%) was identified as the most influential factor affecting maintenance costs, followed by the lack of preventive maintenance implementation (17.2%) and unfavorable operating conditions (15.1%). Together, these three variables accounted for more than half of the model's explanatory power. These findings indicate that a substantial proportion of maintenance costs is attributable to machinery aging, deficiencies in maintenance planning, and improper operating practices rather than to unavoidable equipment deterioration alone.

Furthermore, the results of the Pearson correlation analysis and one-way analysis of variance (ANOVA) revealed that increasing machine age and unfavorable operating conditions were significantly associated with higher maintenance and repair costs. Conversely, systematic implementation of preventive maintenance programs, adoption of Computerized Maintenance Management Systems (CMMS), and improvements in operator skills significantly reduced maintenance costs. These findings indicate that a considerable proportion of maintenance expenditures can be prevented through better maintenance planning, workforce training, and the adoption of modern maintenance technologies.

Moreover, the findings demonstrate that increasing maintenance and repair costs directly undermine the economic sustainability of rural areas by increasing agricultural production costs, reducing farm profitability, limiting opportunities for reinvestment, slowing machinery replacement, and decreasing capital productivity. Conversely, implementing preventive maintenance systems, adopting intelligent maintenance management technologies, strategically replacing aging machinery, and improving operators' technical knowledge can reduce operating costs while increasing machinery productivity, strengthening farm resilience, and promoting sustainable rural development. Therefore, agricultural machinery maintenance management should be regarded as one of the fundamental pillars of agricultural mechanization policies and rural economic sustainability.

The findings of the present study are generally consistent with those reported in both national and international research while extending previous work through a more comprehensive analytical framework and the application of machine-learning techniques. Consistent with Kedir Busse et al. (2026), machine age was identified as the most influential determinant of maintenance and repair costs, confirming that aging machinery increases equipment failures, repair frequency, and life-cycle costs. Similarly, the importance of preventive maintenance supports the findings of Soltanali and Khojastehpour (2023), who demonstrated that systematic maintenance programs improve machinery availability and reduce maintenance expenditures. The results are also consistent with Karimikia and Mohammadi (2025), who emphasized the importance of effective machinery management for improving productivity and reducing production costs. Furthermore, the findings support recent international studies (Shen et al., 2025; Soleimani et al., 2025; Wang et al., 2024; Hertwich et al., 2025), which highlighted the role of intelligent maintenance technologies and data-driven management in improving machinery performance and reducing life-cycle costs.

Although the findings are generally consistent with previous studies, several important differences distinguish the present research from earlier investigations. Most previous studies examined technical, managerial, or operational factors separately or relied primarily on conventional statistical techniques. Consequently, they provided limited evidence regarding the relative importance of multiple interacting factors. By contrast, the present study simultaneously analyzed technical, managerial, operational, human, and environmental variables using the XGBoost algorithm and real machine-year observations, enabling the identification of complex nonlinear relationships and the objective ranking of factor importance. Moreover, unlike previous studies that focused mainly on machinery performance or maintenance efficiency, this research explicitly linked maintenance cost drivers with the economic sustainability of rural areas. Therefore, the present study not only confirms previous evidence but also extends existing knowledge by providing an integrated analytical framework that combines machine learning, real operational data, and sustainability-oriented decision support. In conclusion, the present study demonstrates that maintenance and repair costs are primarily driven by machinery age, preventive maintenance implementation, and operating conditions, while managerial, human, and environmental factors provide important complementary contributions. By integrating qualitative evidence, real machine-year observations, and the XGBoost machine-learning algorithm, this study provides a robust framework for identifying and prioritizing the determinants of maintenance costs. The findings offer practical guidance for policymakers and farm managers seeking to improve maintenance management, reduce production costs, enhance machinery productivity, and strengthen the economic sustainability of rural areas in western Iran.

Practical and Policy Implications- The findings of this study have important implications for agricultural policymakers, extension organizations, machinery service centers, and farm managers in the western provinces of Iran (Kermanshah, Ilam, and Kurdistan). At the policy level, machinery modernization programs, subsidized credit facilities, and replacement incentives should prioritize aging agricultural machinery because machine age was identified as the strongest driver of maintenance costs. At the managerial level, agricultural extension organizations and machinery service centers should strengthen preventive maintenance programs, encourage the adoption of Computerized Maintenance Management Systems (CMMS), improve spare-parts supply chains, and provide continuous technical training for machinery operators. Implementing these measures can reduce machinery downtime, lower production costs, improve farm profitability, and strengthen the long-term economic sustainability of rural communities in western Iran.

Suggestions derived from this research include:

1. Development of a targeted machinery renewal program based on equipment age: The XGBoost results identified machine age as the most influential factor affecting maintenance and repair costs, accounting for 18.9% of the total model importance. Therefore, machinery replacement policies in the provinces of Kermanshah, Ilam, and Kurdistan should prioritize older machines with high repair frequency and declining operational efficiency. Instead of general machinery replacement programs, financial support and low-interest credit facilities should be directed toward farmers operating aged equipment to reduce life-cycle maintenance costs and improve economic sustainability.

2. Establishment of systematic preventive maintenance programs at farm level: The lack of preventive maintenance implementation was ranked as the second most important factor, with a contribution of 17.2% to the model importance. Therefore, agricultural production units should move from reactive repair practices toward scheduled preventive maintenance based on actual machinery operating hours and manufacturer recommendations. Establishing maintenance calendars, recording service histories, and conducting periodic inspections can reduce unexpected failures, decrease repair expenditures, and extend machinery service life.

3. Improvement of machinery operating conditions and operator practices: Unfavorable operating conditions represented the third most influential factor in the XGBoost model, with an importance value of 15.1%. Accordingly, improving machinery utilization practices should be considered a priority management strategy. Training programs should focus on preventing overloading, inappropriate operation under unsuitable field conditions, and improper use of machinery during critical agricultural operations. These measures can reduce mechanical stress, minimize premature component failure, and decrease maintenance costs.

4. Optimization of spare parts supply and maintenance support systems: Spare parts lead time accounted for 9.8% of the total model importance, indicating its significant role in increasing maintenance costs. Therefore, regional maintenance support networks should be developed in the studied provinces through improved spare parts availability, establishment of local inventories for frequently replaced components, and better coordination between farmers, repair centers, and suppliers. Reducing spare parts waiting times can decrease machinery downtime, prevent delays during sensitive agricultural seasons, and improve the economic efficiency of agricultural production systems.

Author Contributions

The authors contributed equally to the development and preparation of this research.

Conflict of Interest

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

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Original Article

رتبه‌بندی محرک‌های هزینه‌های نگهداری ماشین‌آلات کشاورزی و تأثیر آنها بر پایداری اقتصادی روستایی در غرب ایران

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چکیده مبسوط

۱. مقدمه

توسعه پایدار روستایی تا حد زیادی به بهره‌وری و پایداری اقتصادی فعالیت‌های کشاورزی وابسته است. در این میان، مکانیزاسیون کشاورزی با افزایش بهره‌وری عملیات، کاهش نیاز به نیروی کار و بهبود استفاده از منابع، نقش مهمی در تقویت اقتصاد روستایی دارد. بااین‌حال، افزایش هزینه‌های نگهداری و تعمیر ماشین‌آلات کشاورزی، به‌ویژه در شرایط فرسودگی ناوگان، محدودیت منابع مالی، افزایش قیمت قطعات یدکی و دشواری دسترسی به خدمات تخصصی، به یکی از چالش‌های مهم تولیدکنندگان کشاورزی تبدیل شده است. افزایش این هزینه‌ها ضمن کاهش سودآوری، ظرفیت سرمایه‌گذاری مجدد و نوسازی ماشین‌آلات را محدود کرده و در نهایت پایداری اقتصادی خانوارها و سکونتگاه‌های روستایی را تضعیف می‌کند. اگرچه مطالعات پیشین عوامل متعددی همچون سن ماشین‌آلات، شرایط بهره‌برداری، اجرای نگهداری پیشگیرانه، مدیریت قطعات یدکی، مهارت اپراتور و مدیریت نگهداری را شناسایی کرده‌اند، بخش عمده آنها عوامل فنی، مدیریتی یا عملیاتی را به‌صورت جداگانه بررسی کرده و از روش‌های آماری متعارف استفاده نموده‌اند. در نتیجه، شواهد محدودی درباره اهمیت نسبی عوامل متعدد و روابط غیرخطی میان آنها وجود دارد. پژوهش حاضر با هدف شناسایی و رتبه‌بندی عوامل مؤثر بر هزینه‌های نگهداری و تعمیر ماشین‌آلات کشاورزی و تبیین پیامدهای آنها برای پایداری اقتصادی مناطق روستایی غرب ایران انجام شده است. نوآوری اصلی پژوهش، تلفیق دانش خبرگان، داده‌های واقعی ماشین-سال و الگوریتم یادگیری ماشین XGBoost در یک چارچوب تحلیلی یکپارچه است.

۲. مبانی نظری تحقیق

چارچوب نظری پژوهش بر تلفیق «نظریه چرخه عمر دارایی» و «نظریه قابلیت اطمینان و تعمیرپذیری» استوار است. نظریه چرخه عمر دارایی بر این اصل تأکید دارد که عملکرد و هزینه‌های یک دارایی در تمام مراحل عمر آن، از خرید و بهره‌برداری تا نگهداری، نوسازی و جایگزینی، شکل می‌گیرد؛ بنابراین تمرکز صرف بر هزینه اولیه خرید ماشین‌آلات نمی‌تواند هزینه واقعی چرخه عمر را تبیین کند. در این چارچوب، افزایش سن ماشین‌آلات و نزدیک‌شدن آنها به پایان عمر مفید، اهمیت تصمیمات مربوط به نگهداری، بازسازی و جایگزینی را افزایش می‌دهد. در مقابل، نظریه قابلیت اطمینان و تعمیرپذیری بر رابطه میان نرخ خرابی، زمان توقف، شرایط بهره‌برداری، سهولت تعمیر و هزینه‌های نگهداری تأکید دارد. بر این اساس، افزایش خرابی و پیچیدگی تعمیرات، هزینه‌های نگهداری و تعمیر را افزایش می‌دهد؛ درحالی‌که نگهداری پیشگیرانه، پایش وضعیت، مهارت نیروی انسانی و نظام‌های مدیریت نگهداری می‌توانند قابلیت اطمینان ماشین‌آلات را افزایش و هزینه‌های چرخه عمر را کاهش دهند. تلفیق این دو دیدگاه امکان تحلیل هم‌زمان ویژگی‌های فنی و چرخه عمر ماشین‌آلات با عوامل مدیریتی و عملیاتی و پیامدهای اقتصادی آنها را فراهم می‌کند.

۳. روش تحقیق

پژوهش حاضر از نظر هدف، کاربردی و از نظر طرح، توصیفی ـ پیمایشی و با رویکرد آمیخته کیفی ـ کمی انجام شده است. قلمرو مکانی تحقیق شامل مناطق روستایی استان‌های کرمانشاه، ایلام و کردستان است. در مرحله کیفی، ابتدا با مرور نظام‌مند مطالعات، ۴۷ عامل اولیه در چهار حوزه فنی ـ تجهیزاتی، مدیریتی، انسانی و محیطی ـ عملیاتی شناسایی شد. سپس برای بومی‌سازی و پالایش عوامل، با ۲۴ نفر از خبرگان مکانیزاسیون کشاورزی به شیوه نمونه‌گیری هدفمند مصاحبه نیمه‌ساختاریافته انجام شد. تحلیل مضمون مصاحبه‌ها به استخراج ۱۲۸ کد اولیه، ۱۸ مقوله فرعی و چهار مضمون اصلی منجر شد و در نهایت، با توجه به قابلیت اندازه‌گیری و دسترسی به داده‌های معتبر، متغیرهای قابل استفاده در تحلیل کمی انتخاب شدند. در مرحله کمی، اطلاعات واقعی نگهداری و تعمیرات ۸۰ دستگاه ماشین‌آلات کشاورزی دارای سوابق کامل در یک دوره سه‌ساله گردآوری شد. واحد تحلیل «ماشین-سال» و حجم

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داده‌ها ۲۴۰ مشاهده بود. پس از تحلیل‌های توصیفی و محاسبه ضریب همبستگی پیرسون، الگوریتم (XGBoost) برای مدل‌سازی هزینه‌های نگهداری و تعمیر و رتبه‌بندی اهمیت متغیرها به کار گرفته شد. داده‌ها به دو بخش آموزشی ۸۰ درصدی و آزمون ۲۰ درصدی تقسیم شدند و اهمیت متغیرها با معیار Gain سنجیده شد.

۴. یافته‌های تحقیق

یافته‌های مرحله کیفی نشان داد که هزینه‌های نگهداری و تعمیر حاصل تعامل مجموعه‌ای از عوامل است و نمی‌توان آن را صرفاً به فرسودگی ماشین‌آلات نسبت داد. از میان ۱۲۸ کد استخراج‌شده، عوامل مدیریتی با ۳۰.۵ درصد و عوامل فنی ـ تجهیزاتی با ۲۸.۱ درصد بیشترین فراوانی را داشتند و پس از آنها عوامل انسانی با ۲۱.۱ درصد و اقتصادی ـ محیطی با ۲۰.۳ درصد قرار گرفتند. مهم‌ترین مسائل شناسایی‌شده شامل نبود برنامه نوسازی ناوگان، ضعف برنامه‌ریزی تعمیرات اساسی، ناکارآمدی مدیریت قطعات یدکی، نبود سیستم مدیریت نگهداری رایانه‌ای(CMMS)، فرسودگی ماشین‌آلات، عدم اجرای نگهداری پیشگیرانه، شرایط سخت بهره‌برداری، کمبود نیروی متخصص و محدودیت‌های مالی بود. نتایج تحلیل کمی نیز بر اهمیت عوامل فنی، عملیاتی و مدیریتی تأکید کرد. بیشترین همبستگی مثبت با هزینه‌های نگهداری و تعمیر مربوط به سن ماشین‌آلات (۰.۷۸۱) و شرایط بهره‌برداری (۰.۷۵۳) بود؛ درحالی‌که اجرای نگهداری پیشگیرانه با ضریب ۰.۷۴۲- رابطه منفی و قوی با هزینه‌ها داشت. مدل XGBoost عملکرد پیش‌بینی مطلوبی نشان داد و در داده‌های آزمون به ضریب تعیین ۰.۸۶، RMSE برابر ۳۹.۴ میلیون ریال و MAE برابر ۲۸.۷ میلیون ریال دست یافت. رتبه‌بندی بر اساس معیار Gain نشان داد که سن ماشین‌آلات (۱۸.۹ درصد)، عدم اجرای نگهداری پیشگیرانه (۱۷.۲ درصد) و شرایط نامطلوب بهره‌برداری (۱۵.۱ درصد) سه عامل اصلی هستند و در مجموع ۵۱.۲ درصد اهمیت مدل را تشکیل می‌دهند. پس از آنها، زمان تأمین قطعات یدکی (۹.۸ درصد)، استفاده از CMMS(۸.۵ درصد)، ساعات کار سالانه (۷.۸ درصد)، مهارت اپراتور (۶.۹ درصد) و شرایط محیطی (۵.۸ درصد) قرار گرفتند.

۵. بحث و نتیجه‌گیری

نتایج نشان می‌دهد که هزینه‌های نگهداری و تعمیر ماشین‌آلات کشاورزی پدیده‌ای چندبعدی است که بیش از همه تحت تأثیر سن ماشین‌آلات، اجرای نگهداری پیشگیرانه و شرایط بهره‌برداری قرار دارد. این یافته با چارچوب نظری چرخه عمر دارایی و قابلیت اطمینان و نیز نتایج مطالعات پیشین همخوان است، اما پژوهش حاضر با استفاده هم‌زمان از داده‌های واقعی ماشین-سال و XGBoost، امکان شناسایی روابط پیچیده و رتبه‌بندی عینی اهمیت عوامل را فراهم کرده است. همچنین، پیوند مستقیم هزینه‌های نگهداری با پایداری اقتصادی روستایی، وجه تمایز مهم این مطالعه محسوب می‌شود. از منظر سیاستی، نوسازی تدریجی ماشین‌آلات فرسوده، استقرار برنامه‌های نظام‌مند نگهداری پیشگیرانه، بهبود شرایط بهره‌برداری، مدیریت بهینه زنجیره تأمین قطعات یدکی، توسعه سیستم‌های CMMS و آموزش مستمر اپراتورها باید در اولویت قرار گیرد. به‌ویژه، سیاست‌های تسهیلات اعتباری و مشوق‌های نوسازی بهتر است ماشین‌آلات با سن بالا و هزینه تعمیرات زیاد را هدف قرار دهند. اجرای این اقدامات می‌تواند با کاهش توقف ماشین‌آلات و هزینه تولید، افزایش سودآوری و ظرفیت سرمایه‌گذاری مجدد کشاورزان و در نهایت تقویت پایداری اقتصادی فعالیت‌های کشاورزی، به توسعه پایدار مناطق روستایی غرب ایران کمک کند.

کلیدواژه‌ها: ماشین‌آلات کشاورزی، هزینه‌های نگهداری و تعمیر، الگوریتم XGBoost، پایداری اقتصادی، توسعه روستایی، مکانیزاسیون کشاورزی.

تشکر و قدردانی

مطالعه حاضر حامی مالی نداشته و حاصل فعالیت علمی نویسنده است.

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