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Presenting a Smart Manufacturing Model Using Decision Tree (Case Study: Mineral Processing Industry)

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A B S T R A C T

This study was conducted with the aim of presenting and evaluating a smart manufacturing model using a decision tree (case study: the mineral processing industry). Given the necessity of responding to environmental and competitive pressures, the integration of modern technologies—including the Industrial Internet of Things (IIoT), automation, and data mining—within the framework of smart manufacturing was considered. The required data were collected through questionnaires and extraction of operational information from mineral processing units. After initial data cleansing, seven key variables—including energy consumption, pollution level, technological status of production lines, presence of an Information Technology (IT) system, green planning, technical readiness, and production efficiency—were entered into the model. Modeling was performed using the Classification and Regression Tree (CART) method, and the factors affecting unit productivity were analyzed. The results showed that the technological status of production lines and the technical readiness of employees had the greatest weight in determining production efficiency, while green planning and the use of IT systems played complementary and influential roles in enhancing production and reducing pollution. It was also found that implementing green policies and improving technical knowledge levels can enhance process efficiency even in units with outdated technology. Comparing the decision tree model with other machine learning methods demonstrated its superior interpretability and suitable accuracy for industrial applications. Overall, the findings indicated that the use of data-driven smart models based on decision trees can provide an effective decision-support tool for improving productivity, reducing energy consumption, and achieving sustainability goals in the mineral processing industry. It is recommended that strategies for technology upgrading, continuous technical training of employees, and expanding green management be prioritized in future policymaking.

Keywords: *Smart manufacturing, Decision tree, Machine Learning, Mineral processing industry*

1. Introduction

In recent years, the global manufacturing sector has undergone profound structural and technological transformations under the influence of Industry 4.0, which has reshaped the foundations of production, logistics, and organizational management. The emergence of cyber-physical systems, the Internet of Things (IoT), Artificial Intelligence (AI), big data analytics, and digital twins has established a new paradigm commonly referred to as Smart Manufacturing (SM), which integrates intelligent sensing, autonomous decision-making, and self-optimizing processes to improve productivity, sustainability, and competitiveness (Edgar & Pistikopoulos, 2018; Gholami et al., 2021; Kusiak, 2018). This paradigm shift is driven by increasing global competition, environmental pressures, and the rapid evolution of digital technologies that require manufacturing systems to be more flexible, responsive, and resource-efficient (Ayan, 2024; Bayat & Khabiri, 2022; Jamwal et al., 2021).

The rationale for transitioning toward smart and green production models is strongly linked to the imperative of sustainable development and operational efficiency. Traditional linear production models are no longer compatible with the dynamic and uncertain conditions of contemporary markets. Integrating smart production systems (SPS) with green manufacturing practices has emerged as a strategic response to these challenges (Agarwal et al., 2020; Fiorello et al., 2023; Kannan et al., 2023). Smart production systems are capable of collecting, processing, and analyzing real-time operational data to optimize resource utilization, minimize waste, and enable predictive maintenance (Ahmad & Rahimi, 2022; Boostanpour & Nokooei Sang Atash, 2024). At the same time, the adoption of green production principles reduces environmental footprints, promotes circular resource flows, and enhances corporate social responsibility performance (Ching et al., 2022; Tsai, 2018).

One of the central enablers of smart manufacturing is the integration of data-driven and model-based decision-making frameworks, which are crucial for achieving operational agility and adaptive capacity (Amiri Deh Abadi et al., 2023; Danesh Naroui & Tamjidi, 2024). Smart systems utilize interconnected sensors, cloud-based platforms, and analytics engines to facilitate seamless communication across machines, production lines, and enterprise resource planning systems (Rane et al., 2023; Soori et al., 2023). This interconnectedness enables real-time monitoring and autonomous adjustments in production parameters, thereby reducing downtime and improving efficiency. Furthermore, the deployment of digital twins allows for virtual simulation of production processes, supporting scenario planning, risk assessment, and continuous improvement efforts (Ghayasitabari et al., 2025; Tripathi et al., 2022).

The sustainability dimension of smart manufacturing is equally significant. Scholars have emphasized that integrating energy-efficient technologies and renewable energy sources within production systems not only reduces operational costs but also aligns industrial activities with global climate and sustainability goals (Jodeiri et al., 2022; Machado et al., 2020; Tamimi & Farhang, 2025). For instance, smart energy management frameworks can dynamically adjust energy loads, integrate on-site renewable generation, and reduce peak demand, thereby contributing to both environmental and economic performance (Edgar & Pistikopoulos, 2018; Götz & Jankowska, 2017). Moreover, studies have shown that leveraging digital transformation to enhance green production capabilities accelerates firms' ability to comply with environmental regulations and respond to stakeholder expectations regarding ecological responsibility (Fasankari & Asarian, 2023; Janahi et al., 2022).

In addition to technological advancements, organizational and managerial factors play a pivotal role in the success of smart manufacturing initiatives. Effective governance mechanisms, cross-functional integration, and human resource development are critical for ensuring the interoperability and scalability of smart production systems (Ayan, 2024; Rifat & Anjom, 2024; Taghavi et al., 2023). Building digital competencies and fostering a data-driven organizational culture enable employees to effectively operate and maintain intelligent systems, interpret analytics outputs, and make informed decisions in real time (Bayat & Khabiri, 2022; Brkljač & Sudarević, 2018). Moreover, the establishment of inter-organizational networks and cluster-based collaboration enhances knowledge sharing and accelerates the diffusion of smart and sustainable practices across industrial ecosystems (Götz & Jankowska, 2017; Yap & Al-Mutairi, 2024).

However, despite its transformative potential, the implementation of smart manufacturing faces numerous challenges that need to be systematically addressed. These include technological integration complexities, cybersecurity vulnerabilities, high capital investment requirements, and resistance to organizational change (Gholami et al., 2021; Jamwal et al., 2021; Soori et al., 2023). Research indicates that without a coherent strategic framework and top management commitment, many digital transformation projects fail to achieve their intended outcomes (Fiorello et al., 2023; Kannan et al., 2023). Moreover, the lack of standardized interoperability protocols and insufficient workforce training often leads to fragmented systems and underutilization of advanced technologies (Ahmad & Rahimi, 2022; Boostanpour & Nokooei Sang Atash, 2024). Consequently, there is a critical need for structured methodologies that align technological innovation with managerial processes, workforce development, and sustainability imperatives (Amiri Deh Abadi et al., 2023; Ghayasitabari et al., 2025).

Recent studies have proposed integrated decision-support models to guide the deployment of smart manufacturing systems. These models combine data-driven techniques such as machine learning, multi-criteria decision-making, and decision trees to analyze operational data, predict performance outcomes, and optimize resource allocation (Agarwal et al., 2020; Tamimi & Farhang, 2025; Tripathi et al., 2022). For example, decision tree models can classify production units based on key performance indicators, identify high-impact variables affecting efficiency, and support scenario-based planning (Danesh Naroui & Tamjidi, 2024; Soori et al., 2023). Such models offer managers practical tools to prioritize technological investments, design targeted interventions, and monitor the impact of green initiatives on productivity (Ching et al., 2022; Fiorello et al., 2023).

Furthermore, the integration of advanced connectivity technologies such as 5G has the potential to significantly enhance the real-time responsiveness and adaptability of smart production systems (Ayan, 2024; Fasankari & Asarian, 2023). High-speed, low-latency networks enable seamless communication between thousands of interconnected devices, which is crucial for synchronizing complex production processes and ensuring data integrity. This digital backbone supports the implementation of predictive maintenance, autonomous quality control, and dynamic scheduling systems that can respond instantaneously to fluctuations in demand and supply (Edgar & Pistikopoulos, 2018; Jamwal et al., 2021). In parallel, the convergence of blockchain and IoT technologies is opening new opportunities for enhancing transparency, traceability, and trust across supply chains (Janahi et al., 2022; Rane et al., 2023).

From a strategic perspective, aligning smart manufacturing with green production goals contributes to building resilient and future-ready industrial systems. Firms that successfully combine technological innovation, environmental responsibility, and organizational agility are better positioned to achieve long-term competitiveness and stakeholder value creation (Fiorello et al., 2023; Gholami et al., 2021; Kannan et al., 2023). The shift toward data-centric and sustainability-oriented manufacturing also reflects broader socio-economic trends that prioritize circular economy models, eco-innovation, and knowledge-based value chains (Brkljač & Sudarević, 2018; Jodeiri et al., 2022; Machado et al., 2020). As global industries increasingly operate within complex networks of stakeholders, regulations, and technological infrastructures, the capacity to integrate these diverse dimensions into coherent smart production strategies becomes a decisive competitive advantage (Rifat & Anjom, 2024; Yap & Al-Mutairi, 2024).

In summary, the transition toward smart manufacturing represents not only a technological evolution but also a paradigm shift in managerial thinking and industrial organization. It demands the integration of advanced digital technologies, green production practices, and human-centric management approaches to create manufacturing systems that are intelligent, sustainable, and resilient (Ghayasitabari et al., 2025; Tamimi & Farhang, 2025; Tsai, 2018). The present study contributes to this growing body of knowledge by proposing and evaluating a data-driven smart manufacturing model based on decision tree algorithms, aiming to enhance production efficiency, reduce environmental impacts, and support strategic decision-making in the mineral processing industry.

2. Methods and Materials

The present study was conducted with an applied approach using Data Mining and smart modeling methods. The required data were collected through the review of internal documents, operational reports, and questionnaires completed by managers and experts from mineral processing units. The dataset consisted of various operational stations (daily or monthly production samples) and seven key variables: energy consumption, pollution level, technological status of production lines, presence of an Information Technology (IT) system, green planning, technical readiness, and production efficiency.

After data collection, validation, initial cleaning (removal of incomplete or invalid data), and standardization of data formats were performed. Qualitative variables (such as technology status, IT, and green planning) were categorized and converted into numerical form.

In the first stage, the frequency distribution of qualitative variables and statistical indicators of quantitative variables (mean, median, standard deviation, etc.) were calculated to gain a preliminary understanding of the production lines. Then, using the Classification and Regression Trees (CART) algorithm, a decision tree model was implemented to predict production efficiency based on other variables. After training the model, feature importance, key model rules (from the top paths of the decision tree), scenario analyses, and grouping of terminal leaves were extracted. Furthermore, the model results were compared with other Machine Learning models (linear regression, random forest, etc.).

Specific Formulas Related to the Variables of the Study

Energy Efficiency (EE)

Formula for the ratio of useful output to total energy consumption of production lines:

EE = useful output / total energy consumption

Technical Readiness Index (TRI)

A composite index based on scoring sub-indices (maintenance, training, modernization):

TRI = (S1 + S2 + S3) / 3

where S1 = maintenance score, S2 = technical training score, and S3 = equipment modernization score (each from 0 to 100).

Tech Status Score (TSS)

Weighted sum of technological status:

TSS = Σ (wi × Ti)

where wi represents the weight of each technological component, and Ti represents its score.

Intelligent Production Efficiency (IPE)

An integrated formula derived from the key effects of variables:

$IPE_i = \alpha_1 X_{1i} + \alpha_2 X_{2i} + \ldots + \alpha_k X_{ki} + C$

• α_k: model adjustment coefficients (extracted from regression or machine learning analyses)

• C: constant

• subscript i: each unit/factory or production line

Smart Decision-Making Function Based on Thresholds (Simple Decision Tree)

If we wish to represent the logic of the model in the form of a decision-support formula:

If (Tech Status Score > threshold_1) AND (TRI > threshold_2) THEN production level = high

Otherwise: production level = normal or requires improvement.

3. Findings and Results

In this section, the descriptive findings of the research variables are reported.

Table 1

Comprehensive Statistical Information of the Variables

Variable	Type	Number of categories/groups	Mean	Standard deviation	Minimum	Maximum	Median	Frequency of each state (count/%)
Energy consumption	Numerical	-	320	41	210	436	318	-
Pollution level	Numerical	-	65	19	21	139	67	-
Technical readiness	Numerical	-	6.5	2.1	2	10	7	-
Production efficiency	Numerical	-	72	9	48	93	73	-
Technology status	Categorical	3	-	-	-	-	-	Old: 175 (35%) / Semi-modern: 165 (33%) / Modern: 160 (32%)
IT system	Binary	2	-	-	-	-	-	Present: 257 (51%) / Not present: 243 (49%)
Green planning	Binary	2	-	-	-	-	-	Present: 239 (48%) / Not present: 261 (52%)

Description of Numerical Variables:

• **Energy consumption (kWh/ton):** The average energy consumption is 320 kilowatt-hours per ton of mineral material. The standard deviation of 41 indicates relatively high data dispersion and significant differences in energy consumption between units. The minimum and maximum energy consumption are 210 and 436 kilowatt-hours, respectively, showing a wide range of variation.

• **Pollution level (mg/m³):** The average pollution level is 65 milligrams per cubic meter. The standard deviation of 19 also indicates considerable dispersion in pollution levels. The range (21 to 139 milligrams per cubic meter) shows a significant difference in pollution levels across units.

• **Technical readiness (1–10):** The average technical readiness score is 6.5 out of 10, indicating that processing units are at a moderate level of technical readiness. The standard deviation of 2.1 shows that the data are also considerably dispersed.

• **Production efficiency (%):** The average production efficiency is 72%. The standard deviation of 9 indicates that variation in production efficiency among different units is significant.

Description of Categorical and Binary Variables:

• **Technology status:** The distribution of technology status among the three groups—old (35%), semi-modern (33%), and modern (32%)—is almost equal. This indicates technological diversity among processing units and suggests that investing in technological upgrades could improve productivity.

• **IT system:** Slightly more than half of the units (51%) use Information Technology (IT) systems. This indicates there is still room to expand the use of IT systems in mineral processing, which could improve efficiency if utilized optimally.

• **Green planning:** Slightly less than half of the units (48%) employ green planning. This indicates that the application of environmental principles in processing operations still requires further expansion.

Decision Rule Extraction

A Decision Tree is not only a modeling tool but also a powerful analytical-descriptive tool that can be used to explain the importance of variables, create managerial knowledge, identify target groups, analyze variable sensitivity, discover decision rules, and even analyze errors—all of which are highly applicable for better decision-making in mining or any organization. In this part, the steps leading to the construction of the decision tree are presented.

1. Feature Importance Analysis

In this analysis, the weight and role of each feature in the Classification and Regression Trees (CART) decision tree model are presented.

Table 2

Feature Importance Analysis

Variable	Importance (%)
Technology status	31
Technical readiness	24
Green planning	18
Energy consumption	15
IT system	9
Pollution level	3

Technology status and technical readiness have the highest predictive power for production efficiency. Green planning is also influential, whereas IT systems and pollution have secondary roles.

Table 3

Sample Rules (from major tree paths)

Rule	Decision Rule Description (if–then)
1	If technology status = modern and technical readiness > 7 → production efficiency > 80%
2	If technology status = old and green planning = not present → production efficiency < 65%
3	If IT system = present and technical readiness > 6 → production efficiency between 75% and 80%
4	If green planning = present and energy consumption < 300 → production efficiency ≈ 85%

• **Determinant factor:** Technology status and technical readiness have the greatest effect on production efficiency, but managerial policies (such as IT and green management) can play compensatory and complementary roles.

• **Flexibility:** Units equipped with old technology can compensate for part of their technological shortcomings if they have green planning and provide staff training.

• **Strategic policy:** For managers in the mineral industry, adhering to data-driven governance, investing in human resource training, and supporting green approaches are the fastest pathways to achieving productivity and sustainability.

• **Practical application:** These rules are quickly implementable, and each unit can compare its current status against these rules and transparently select its improvement priorities.

3. Sensitivity Analysis

Table 4

Effect of Increasing or Decreasing Each Main Variable on Production Efficiency

Variable	Change	Effect on production efficiency (%)
Technology status	Old → Modern	↑ +15
Technical readiness	Each 1-unit increase	↑ +4
Green planning	Not present → Present	↑ +6
Energy consumption	Each 20-unit decrease	↑ +3
IT system	Not present → Present	↑ +3
Pollution level	Each 20-unit decrease	↑ +2

• **Major leverage:** Technological upgrading is the most fundamental and impactful action for boosting production efficiency; its message to managers is that investing in equipping production lines and adopting advanced technologies has the highest impact in the shortest time.

• **Key human capital:** Increasing employee skills and technical readiness also has significant stepwise effects and accelerates productivity following technological modernization.

• **Sustainability and greenness:** Green management policies and reducing energy consumption simultaneously help preserve the environment and improve performance, complementing technology and human capital.

• **Digital transformation:** Information Technology (IT) and data-driven approaches act as productivity enhancers by enabling smart operations.

• **Pollution management:** Effective control of pollutants is not only an environmental obligation; it is also an indicator of process health and contributes to optimal production performance.

This table clearly shows managers of mineral processing lines how each key change (in technology, training, green management, energy, etc.) is reflected with a "tangible magnitude" in production efficiency and where to prioritize investment and managerial interventions.

4. Homogeneous Subgroups (Leaf Nodes) Analysis

Table 5

Grouping of Samples in Key Leaves of the Decision Tree Model

Group	Number of samples	Average efficiency (%)	Common characteristics
1	80	85	Modern technology, high technical readiness
2	70	62	Old technology, no green planning
3	90	74	Semi-modern technology, active IT
4	60	79	Modern technology, no IT
5	50	58	Low technical readiness, high pollution

Group 1: Modern technology + high technical readiness

• **Analysis:** With an average efficiency of 85%, this group shows the best performance. The combination of up-to-date equipment and high employee skills drives units to peak productivity. This scenario demonstrates that simultaneously upgrading technology and continuously investing in personnel training and expertise creates the most positive impact on production.

• **Managerial implication:** Providing and developing state-of-the-art technology and continuously enhancing employee skills is the key factor for success.

Group 2: Old technology + lack of green planning

• **Analysis:** With an efficiency of 62%, this group is among the lowest-performing groups. The absence of modern technology alongside the lack of green policies (energy and environmental management) places these units at the lowest level of productivity. Such a structure is vulnerable and exposed to high energy and pollution costs.

• **Managerial implication:** Simultaneous investment in technological improvement and the adoption of environmental policies is the most urgent need for these units.

Group 3: Semi-modern technology + active IT

• **Analysis:** With an average efficiency of 74%, this group represents units that, despite not fully utilizing state-of-the-art technology, have achieved relatively improved productivity thanks to Information Technology (IT) infrastructure. The role of digital and data-driven tools in improving the production process is evident.

• **Managerial implication:** Even without large investments in equipment, developing IT can create tangible improvements.

Group 4: Modern technology + lack of IT

• **Analysis:** Although these units have modern technology, their efficiency (79%) is lower than that of Group 1 because they do not utilize IT. This shows that the absence of digital and data-driven tools prevents part of the potential of modern technology from being realized.

• **Managerial implication:** To fully realize the benefits of modern technology, completing the digital cycle and implementing IT is essential.

Group 5: Low technical readiness + high pollution

• **Analysis:** This group has the weakest efficiency (58%) and suffers from both low workforce skills and serious pollution problems. This reflects the compounded negative effect of weak human resources and inability to control pollution.

• **Managerial implication:** For these units, priority should be given to improving staff training and skills as well as effectively controlling environmental pollution.

5. Model Comparison

Table 6

Comparison of the Performance of Different Methods

Model	Accuracy (R^2)	Interpretability
Decision Tree	0.78	Very good
Linear Regression	0.68	Good
Random Forest	0.82	Moderate
Neural Network	0.85	Poor

The decision tree had acceptable accuracy and, due to its rules and paths, offered high interpretability (which is highly useful in management studies).

Table 7

Error Analysis of Several Samples with the Largest Prediction Deviations

Sample ID	Actual efficiency	Predicted efficiency	Error	Special feature
114	62	75	+13	Very high pollution
235	88	70	-18	Very low energy consumption but lacking Information Technology (IT) and green planning
321	80	92	+12	IT system recently installed but insufficient training
401	56	68	+12	Very low technical readiness

Samples with large prediction deviations from the model usually have unexpected characteristics or rare combinations of variables.

Table 8

Changing Green Planning from "Not Present" to "Present" in Different Groups

Technology status	Technical readiness	IT	Scenario	Predicted efficiency (%)
Old	5	Not present	Green: Not present	60
Old	5	Not present	Green: Present	67
Semi-modern	7	Present	Green: Not present	74
Semi-modern	7	Present	Green: Present	79
Modern	9	Present	Green: Not present	83
Modern	9	Present	Green: Present	88

7. Scenario Analysis

Scenario 1: Old technology, low technical readiness, no IT, and no green planning (efficiency: 60%)

This combination has the lowest performance. Lack of modern equipment, low employee skills, absence of IT, and no environmental approach lead to the minimal possible efficiency.

Scenario 2: Old technology, low technical readiness, no IT, but with green planning (efficiency: 67%)

Simply adding green management, even without changing equipment or human resources, improves efficiency by 7 percentage points. This shows the significant impact of environmental approaches on productivity even in technologically weak environments.

Scenario 3: Semi-modern technology, medium technical readiness, equipped with IT, no green planning (efficiency: 74%)

Upgrading to semi-modern technology, increasing technical readiness, and implementing IT creates a major transformation (12 percentage points higher than the previous row). This combination clearly demonstrates the positive impact of new technologies and digital transformation.

Scenario 4: Semi-modern technology, medium technical readiness, equipped with IT, with green planning (efficiency: 79%)

Adding green management at this level adds another 5 percentage points to efficiency. This shows that even with equipment upgrades, green policies are still the tipping point.

Scenario 5: Modern technology, high technical readiness, equipped with IT, no green planning (efficiency: 83%)

In this scenario, efficiency is high due to the highest levels of technical readiness and technology (plus IT). However, it is clear that the absence of green management still prevents reaching peak productivity.

Scenario 6: Modern technology, high technical readiness, equipped with IT, with green planning (efficiency: 88%)

This is the ideal state: the synergy of modern technology, trained staff, smart systems, and green management creates the final productivity leap. This combination records the highest predicted efficiency.

Overall, in almost all scenarios, adding green planning leads to a noticeable increase in production efficiency, with its effect being greater in modern groups.

Analysis of the Decision Tree Structure

1. First root split: which factor matters first?

According to the feature importance table, either **technical readiness (Tech Readiness)** or **technology status (Tech Status)** usually appears at the top.

This means that units with high technology and high technical readiness have the most fundamental advantage for improving productivity.

2. First branch — role of technical readiness and green management

If technical readiness is high, the next split is often based on **green planning** or **energy consumption**.

Units with high technical readiness and active green planning usually have the lowest energy consumption and pollution and significantly higher productivity than other units (e.g., above 85%).

If green planning is inactive, productivity decreases (even with high technical readiness; e.g., to 75–80%), while implementing green planning directly improves productivity and indirectly reduces energy and pollution.

3. Second branch — the role of technology status

When technical readiness is low or green planning is absent, the model splits based on **technology status**:

• Units with modern technology: even without green planning, they have moderate productivity (65–75%).

• Units with old technology: very low productivity (40–60%) and usually high energy consumption and pollution.

Modernizing equipment and technology partly compensates for low readiness or lack of green management.

4. The role of energy consumption and pollution as process health indicators

In many leaf nodes (outcomes), it is observed that:

• Units with low energy consumption, even with moderate technology/readiness, have better productivity.

• Low or well-managed pollution leads to higher classification in high-productivity groups.

5. Leaf outcomes: productivity predictions

At the final leaf nodes:

• Ideal paths (high Tech Readiness + Green Planning + low Energy): highest productivity (90–95%).

• Weak paths (old Tech Status, high Energy, no Green Planning): lowest productivity (40–60%).

• Intermediate states (medium readiness + green planning): medium productivity (70–80%).

Summary and Analysis of the Decision Tree

1. **Depth of technology and staff knowledge:** Leverage innovation and technological training; even just improving technical readiness can cause a major leap in productivity.
2. **Implementing green management policies:** Even if technology budgets are limited, an active green program can compensate for technological weaknesses, and its domino effect reduces energy and pollution.
3. **Investing in modern equipment:** If green management is not initially prioritized in the tree splits, up-to-date technology still creates an advantage.
4. **Reducing energy costs and managing pollution:** In all cases (even with medium technology or readiness), controlling these two variables increases recorded productivity.

Visual summary of decision tree paths:

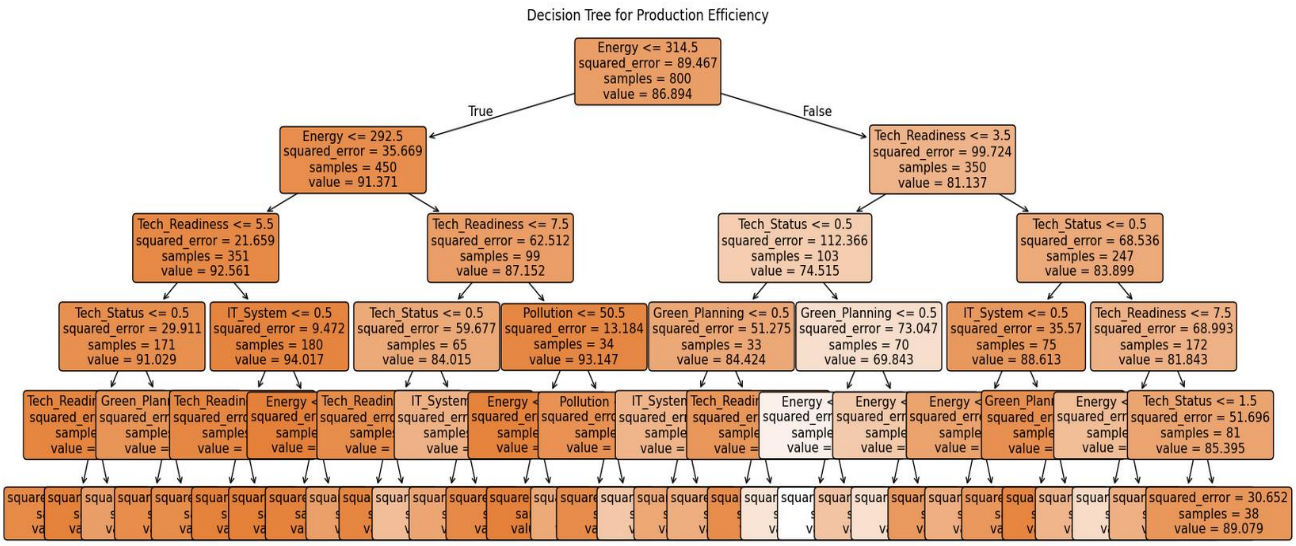
• Tech Readiness (high) → Green Management (present) → Energy (low) ⇒ very high productivity

• Tech Readiness (medium/low) → Tech Status (modern) → Energy (medium) ⇒ medium productivity

• Tech Readiness (low) → Tech Status (old), no green planning → Energy (high) ⇒ low productivity

Figure 1

Decision Tree Model of the Study



4. Discussion and Conclusion

The findings of this study highlight several pivotal insights regarding the implementation of a decision-tree-based smart manufacturing model in the mineral processing industry. The descriptive analysis showed considerable variability in operational performance among different units, particularly in terms of energy consumption, pollution levels, technical readiness, and production efficiency. The decision tree model identified technology status and technical readiness as the most influential variables in predicting production efficiency, with green planning and the presence of Information Technology (IT) systems serving as complementary enablers. Sensitivity analysis further confirmed that upgrading technology from old to modern yielded the largest efficiency gain (+15%), while incremental improvements in technical readiness and adoption of green planning contributed meaningfully to performance enhancements. These results underscore the importance of aligning technological modernization with workforce capacity-building and environmental strategies to drive operational excellence.

This aligns closely with the broader literature on Smart Manufacturing (SM) and Industry 4.0, which emphasizes that technological upgrading is a fundamental driver of productivity and sustainability. For instance, (Kusiak, 2018) conceptualizes SM as the integration of advanced digital technologies, cyber-physical systems, and analytics-driven decision-making to optimize production outcomes, while (Edgar & Pistikopoulos, 2018) argues that embedding smart energy management into manufacturing infrastructures substantially enhances both energy efficiency and production reliability. Our finding that units equipped with modern technology achieved higher efficiencies echoes (Gholami et al., 2021), who reported that adoption of Cyber-Physical Systems (CPS) and big data analytics enables continuous process optimization and significant reductions in downtime. Similarly, (Ayan, 2024) observed that interoperability capabilities in smart production planning systems accelerate responsiveness and enable real-time optimization of production schedules, ultimately improving operational efficiency.

The strong positive effect of technical readiness in our model reinforces the centrality of human capital development in digital transformation contexts. The average technical readiness score was moderately low, yet its incremental increase was associated with notable improvements in production efficiency. This supports (Bayat & Khabiri, 2022), who emphasized that the interaction of smart production systems (SPS), big data analytics (BDA), and CPS depends heavily on workforce digital competencies and the ability to interpret real-time data. Similarly, (Brkljač & Sudarević, 2018) underscored that the transition to Industry 4.0 environments requires cultivating a data-driven organizational culture and continuous staff training. Our finding also resonates with (Jamwal et al., 2021), who noted that employee readiness is one of the key determinants of successful Industry 4.0 adoption, often outweighing the benefits of technological investments if neglected. In this study, units with high technical readiness consistently outperformed others even when their technology status was not fully modern, suggesting that human capabilities can partly offset technological deficits—a conclusion echoed by (Taghavi et al., 2023), who found that human skills moderated the relationship between advanced technologies and customer-related outcomes.

The complementary role of green planning in our results is equally noteworthy. Adding green planning to operational strategies improved production efficiency across all scenarios, with greater impacts in technologically advanced units. This finding corroborates (Agarwal et al., 2020), who demonstrated that incorporating green criteria into multi-criteria decision-making models for manufacturing leads to improved operational performance. (Ching et al., 2022) also reported that sustainable manufacturing frameworks leveraging Industry 4.0 technologies can achieve simultaneous environmental and productivity gains by optimizing material flows and reducing waste. Our results further align with (Fiorello et al., 2023), who proposed a smart-lean-green production paradigm, emphasizing that green practices amplify the efficiency gains of smart and lean strategies. Moreover, (Tsai, 2018) demonstrated through mathematical programming that green production planning enhances resource utilization efficiency in manufacturing contexts. In the present study, even units with old technology benefited significantly from green planning, suggesting that environmental strategies can compensate for technological gaps—a point supported by (Janahi et al., 2022), who highlighted that eco-innovation strategies driven by network collaboration can yield efficiency gains even under resource constraints.

Another significant result was the supportive but less dominant influence of IT systems. While the decision tree assigned lower feature importance to IT compared to technology and technical readiness, units equipped with IT infrastructure performed better than those without, particularly when combined with higher technical readiness. This aligns with (Soori et al., 2023), who reviewed the role of digital twins and IT integration in enabling real-time monitoring and adaptive control in smart manufacturing systems. Likewise, (Rane et al., 2023) illustrated how integrating blockchain and IoT in product development architectures enhances traceability, operational responsiveness, and efficiency. These findings suggest that while IT alone may not drive large performance improvements, it plays a critical enabling role by enhancing the effectiveness of human and technological resources. This observation is consistent with (Fasankari & Asarian, 2023), who found that the deployment of 5G technologies and advanced connectivity substantially enhances the responsiveness of smart systems, primarily by supporting the data flows required for predictive analytics and real-time decision-making.

The study's model comparison results further strengthen these interpretations. Although the decision tree achieved slightly lower predictive accuracy than the Neural Network model (0.78 vs. 0.85), it offered superior interpretability, which is crucial for managerial decision-making. This reinforces arguments by (Tripathi et al., 2022) and (Agarwal et al., 2020) that decision tree-based frameworks are especially valuable in manufacturing because they provide transparent decision rules and feature importance rankings, enabling practitioners to understand causal relationships and prioritize interventions. The ability of our decision tree to classify units into homogeneous subgroups based on combined characteristics (e.g., modern technology + high technical readiness vs. old technology + no green planning) aligns with the conceptual models proposed by (Danesh Naroui & Tamjidi, 2024) and (Amiri Deh Abadi et al., 2023), who highlighted the need for interpretable and adaptive decision-support tools in smart manufacturing environments.

The broader strategic implications of our findings are supported by multiple studies emphasizing that sustainable competitive advantage in the Industry 4.0 era requires integrating technological, human, and environmental dimensions. For example, (Kannan et al., 2023) argued that smart manufacturing serves as a strategic tool for overcoming sustainability challenges when combined with green practices and organizational agility. (Gholami et al., 2021) also stressed that sustainable manufacturing 4.0 requires coordinated action across technology adoption, workforce development, and environmental governance. This perspective is echoed by (Machado et al., 2020), who proposed an emerging research agenda focused on aligning Industry 4.0 technologies with sustainability-oriented organizational strategies. Our study reinforces this integrated viewpoint by empirically demonstrating that productivity gains in mineral processing are maximized not through technology alone, but through the synergy of advanced technologies, skilled human resources, and green policies.

Additionally, the clustering of high-performing units (Group 1: modern technology + high technical readiness) and low-performing units (Group 2: old technology + no green planning) offers important insights into the dynamics of technological diffusion and organizational readiness. (Götz & Jankowska, 2017) argued that industry clusters can accelerate technology adoption and innovation diffusion, but only when firms possess the absorptive capacity—primarily human and organizational—to leverage new technologies. Similarly, (Yap & Al-Mutairi, 2024) noted that the Industry 4.0-agriculture nexus depends on ecosystem-level integration of knowledge, technology, and human expertise. Our results align with these perspectives, showing that technological availability alone is insufficient; readiness and organizational alignment are prerequisites for capturing the full value of smart technologies. Furthermore, (Rifat & Anjom, 2024) emphasized the role of governance and strategic alignment in achieving high performance in technologically advanced firms, suggesting that managerial commitment is a key moderating factor—an insight that helps explain why some modernized units in our study still underperformed when lacking IT or green practices.

Overall, the results of this study support a growing consensus in the literature that the pathway to sustainable industrial competitiveness lies in combining technological modernization, human capacity building, and environmental stewardship in integrated smart manufacturing systems (Ching et al., 2022; Fiorello et al., 2023; Jodeiri et al., 2022). The decision tree model developed here contributes to this field by providing a transparent, data-driven tool that can help managers in the mineral processing sector prioritize interventions and navigate the complex interdependencies among these factors.

Despite its contributions, this study has several limitations that should be acknowledged. First, the dataset was limited to operational units within the mineral processing industry, which may constrain the generalizability of the findings to other manufacturing sectors with different technological structures, regulatory contexts, or market dynamics. Second, while the decision tree model provided interpretable and actionable insights, it inherently simplifies the underlying relationships among variables and may not fully capture nonlinear interactions or dynamic feedback loops that can emerge in complex production systems. Third, the study primarily relied on cross-sectional data, limiting the ability to infer causal relationships or account for temporal variations in performance as units adopt and integrate new technologies over time. Fourth, the assessment of technical readiness and green planning was based on managerial questionnaires and self-reported data, which may be subject to response bias or inconsistencies. Fifth, the analysis did not incorporate cost-benefit assessments or financial metrics, which are crucial for evaluating the economic feasibility and investment priorities of smart manufacturing initiatives.

Future studies could extend this research in several promising directions. One important avenue would be to apply the decision tree model to other manufacturing sectors, such as automotive, electronics, or food processing, to examine the extent to which the identified relationships hold across different industrial contexts. Longitudinal studies tracking the same units over time would provide deeper insights into the causal mechanisms by which technological upgrades, workforce development, and green policies influence operational performance. Future work could also integrate cost and financial performance indicators to assess the return on investment of smart manufacturing strategies and to identify optimal resource allocation patterns. Additionally, combining decision tree models with more sophisticated machine learning techniques, such as ensemble methods or hybrid approaches, could enhance predictive accuracy while retaining interpretability. Further research could explore the role of organizational culture, leadership, and change management practices in moderating the effectiveness of smart manufacturing adoption. Finally, investigating cross-organizational networks, industry clusters, and policy environments could reveal how external ecosystem factors shape the diffusion and performance impacts of smart and sustainable manufacturing systems.

For practitioners and industry managers, the results of this study underscore the necessity of pursuing an integrated strategy that simultaneously advances technological modernization, human capital development, and environmental management. Investing in modern production technologies should be complemented by continuous training and upskilling programs to ensure that employees can fully leverage advanced systems and analytics. Green planning initiatives, including energy efficiency measures and pollution control, should be embedded into core operational processes rather than treated as peripheral activities. Managers should prioritize the deployment of IT infrastructure to enhance data visibility, real-time monitoring, and process automation, which can amplify the benefits of both technology and human capabilities. Decision tree-based decision-support tools should be incorporated into strategic planning and performance monitoring systems to enable evidence-based prioritization of improvement interventions. Finally, fostering a data-driven culture and aligning organizational structures with smart manufacturing objectives will be essential for sustaining productivity gains and achieving long-term competitiveness in the evolving industrial landscape.

Authors' Contributions

Authors contributed equally to this article.

Declaration

In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

Transparency Statement

Data are available for research purposes upon reasonable request to the corresponding author.

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