Future of Work and Digital Management Journal

Article type:
Original Research

Article history:
Received 03 February 2025
Revised 03 May 2025
Accepted 12 May 2025
Published online 21 June 2025

# Machine Learning for Predicting Complex Solutions in Production, Cost, and Financial Performance of Companies

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How to cite this article:
Bahrami, M., Alavi Matin, Y., & Iranzadeh, S. (2025). Machine Learning for Predicting Complex Solutions in Production, Cost, and Financial Performance of Companies. *Future of Work and Digital Management Journal, 3*(2), 1-12.
https://doi.org/10.61838/fwdmj.3.2.9



## ABSTRACT

In recent years, competition among manufacturing companies regarding the provision of goods and products required by customers has been increasing. At present, customers tend to receive their required goods in the shortest possible time and at the lowest possible cost. In this regard, companies that are able to reduce their costs and, at the same time, deliver goods to customers on time and without delay, have a greater ability to attract more customers. Therefore, it can be stated that production planning and scheduling has gained increasing importance compared to the past, and today it plays a significant role in achieving competitive advantage for companies. Accordingly, the present study seeks to utilize machine learning to predict complex solutions. From the perspective of purpose, this research is applied, and in terms of methodology, it is correlational. Regarding data collection, this study is descriptive–analytical and relies on library studies for gathering information. Descriptive research is used to examine current conditions for better understanding in order to support the decision-making process. The statistical population of the present study consists of the Mobarakeh Steel Company of Isfahan. Considering that the research data is quantitative, the data was extracted from existing documents and records. As a result, the sample under study consists of data related to production, cost, and financial performance during the years 2016–2020. The sampling method in this research is purposive. To collect information, both library and field methods were used. Library studies were employed as a foundation for developing the theoretical framework of the research, and the field method was used to obtain data from Mobarakeh Steel Company.

**Keywords:** Machine learning, Production performance, Cost and financial performance, Complex solutions

## Introduction

The unprecedented evolution of global financial markets over the past two decades has placed advanced predictive technologies at the core of research and practice in finance, economics, and management. With increasing volatility, complex risk structures, and rapidly changing regulatory environments, traditional quantitative tools alone have proven insufficient to capture the multifaceted nature of modern financial phenomena. Consequently, artificial intelligence (AI) and machine learning (ML) have emerged as transformative solutions to address challenges in forecasting, risk assessment, portfolio optimization, and financial decision-making. Recent studies demonstrate that ML not only improves predictive accuracy but also incorporates multidimensional data—including textual, behavioral, and environmental information—into decision models, thereby offering new paradigms of efficiency in production, cost management, and financial planning [1, 2].

Financial markets operate as complex adaptive systems in which multiple interacting factors such as investor sentiment, global shocks, corporate fundamentals, and institutional structures co-evolve. Machine learning, with its ability to handle non-linear patterns and high-dimensional datasets, has proven to be a breakthrough in managing such complexity [3]. The integration of ML in financial modeling is not merely a methodological upgrade but a conceptual shift that allows scholars and practitioners to explore relationships previously hidden by the constraints of linear statistical methods [4]. In this context, predictive accuracy in production performance, cost efficiency, and financial risk assessment can significantly enhance competitiveness for firms operating in industries where operational speed and efficiency directly influence survival [5, 6].

A central strand of research highlights the role of ML in financial forecasting and decision support systems. Forecasting stock market behavior has long been regarded as a “grand challenge” due to its inherent unpredictability and susceptibility to external shocks. Recent advancements in supervised learning algorithms, deep learning models, and hybrid AI systems have enabled scholars to overcome several limitations of earlier approaches [7]. The predictive power of ML stems from its capacity to adapt to continuously changing data patterns and identify complex interdependencies between financial indicators [8]. For instance, ensemble learning and neural networks have demonstrated effectiveness in analyzing stock price fluctuations and recognizing graphical trading signals, opening pathways to more robust forecasting practices [9].

Notably, the extension of ML applications beyond stock price forecasting to domains such as bankruptcy prediction, credit scoring, and corporate financial distress analysis has enriched managerial decision-making [10, 11]. The capacity of ML to incorporate both structured financial indicators and unstructured data—such as management reports, textual disclosures, and ESG (environmental, social, and governance) features—marks a paradigm shift in predictive analytics [6, 12]. This convergence reflects an emerging interdisciplinary perspective in which financial, managerial, and sustainability variables are jointly considered for more holistic models of corporate viability.

Risk management, one of the most critical components of financial operations, has also witnessed a dramatic transformation through the deployment of ML. Traditional models, such as ARIMA and GARCH, often fail to fully capture the non-linear dynamics and structural breaks evident in financial data [5]. In contrast, ML models provide flexible frameworks that adapt to changing conditions and offer superior risk prediction. By modeling market volatility, liquidity risks, and systemic shocks, these approaches have enhanced risk-adjusted decision-making at both micro and macroeconomic levels [13].

The banking and financial services sector has particularly benefited from these advances. From fraud detection to customer credit evaluation, ML applications in banking have redefined operational efficiency [14]. Studies highlight how AI-driven credit scoring mechanisms provide more accurate borrower evaluations while reducing biases inherent in conventional systems [15]. Moreover, the integration of blockchain with ML in financial services creates secure, transparent, and efficient platforms that facilitate trust and resilience [16]. These innovations reflect the growing institutional interest in merging emerging technologies with financial infrastructures to address both opportunities and vulnerabilities.

Beyond financial markets, ML has gained traction in predicting operational outcomes related to production efficiency, cost optimization, and financial planning at the firm level. Firms in manufacturing and industrial sectors increasingly rely on predictive analytics to optimize production scheduling, minimize costs, and mitigate financial risks [17]. The integration of ML with decision tree algorithms, support vector machines, and deep learning frameworks enables the detection of patterns in production data that enhance hierarchical planning and improve managerial decision-making [2].

The predictive strength of ML in operational contexts is evident in studies where hierarchical planning systems, supported by ML algorithms, achieved improved production accuracy, minimized waste, and ensured optimal resource allocation [18]. These applications demonstrate that production-related decision-making can no longer rely solely on deterministic models.

Instead, ML offers dynamic simulations and scenario analyses that capture the stochastic nature of production and cost environments. For instance, scenario modeling with ML allows firms to evaluate the impacts of market demand fluctuations, budget adjustments, and inventory policy changes on financial outcomes, thereby providing strategic foresight [19].

Recent literature emphasizes that ML in finance is not confined to algorithmic efficiency but also intersects with behavioral and institutional perspectives. Incorporating behavioral biases into predictive models enables more realistic forecasts of investment decisions, credit risk assessments, and financing strategies [17]. Such integration is essential in environments where managerial and investor behaviors significantly influence market outcomes. The synergy between AI-driven predictions and behavioral finance deepens the understanding of decision-making under uncertainty, creating a more comprehensive analytical lens [3].

Furthermore, the fusion of AI and ML with financial technology (FinTech) underscores their transformative influence on digital financial ecosystems [3]. The interaction between big data analytics, ML, and emerging FinTech services fosters innovations in customer service, payment systems, and regulatory compliance. These advancements not only improve efficiency but also create challenges regarding transparency, ethics, and governance [4]. In this regard, vertical assimilation of ML within institutional structures serves as a safeguard for financial data, ensuring integrity and regulatory compliance in the digital era [19].

An important extension of ML applications involves sustainability and new asset classes. The incorporation of ESG factors into predictive models reflects the growing recognition of environmental and social considerations in financial decision-making. Advanced ML models are increasingly employed to predict clean energy prices and ESG market performance, providing firms and investors with tools to align financial decisions with sustainability goals [12]. Similarly, the rapid growth of cryptocurrencies and digital assets has prompted the use of ML for price prediction and portfolio optimization, particularly in managing high volatility and risk-adjusted returns [2].

This expansion highlights how ML has transcended traditional financial modeling to address broader economic and societal priorities. The dual focus on profitability and sustainability aligns with global imperatives for responsible investment and corporate governance. At the same time, ML models enable robust scenario analyses for emerging markets and asset classes, fostering resilience against uncertainties [1].

Despite these advancements, the application of ML in finance and management is not without challenges. Algorithmic transparency, data quality, interpretability, and ethical considerations remain central issues [13]. For example, black-box models, though highly accurate, often raise concerns about explainability, which is crucial for decision-making in regulated industries [10]. Recent studies propose hybrid models that balance predictive accuracy with interpretability, leveraging tools such as Shapley Additive Explanations (SHAP) to make complex ML models more transparent [10].

Another significant challenge lies in the integration of ML models into organizational decision processes. While predictive power is invaluable, organizational readiness, managerial expertise, and cultural acceptance play critical roles in the successful implementation of AI systems [18]. These considerations highlight the need for interdisciplinary approaches that combine technical sophistication with organizational and behavioral insights [4].

The convergence of ML with financial forecasting, risk management, production optimization, and sustainability creates a powerful toolkit for firms navigating complex environments. The literature reviewed demonstrates that ML not only improves predictive capacity but also broadens the scope of decision-making by incorporating behavioral, textual, and sustainability variables [6, 11]. By enabling accurate scenario modeling and dynamic adjustment, ML equips managers, investors, and policymakers with tools to enhance competitiveness and resilience in uncertain environments [1, 12].

As industries face mounting pressures from globalization, digitalization, and sustainability imperatives, ML's role in shaping the future of finance and management will only intensify. This study contributes to this growing body of knowledge by exploring the predictive capacities of ML in relation to complex solutions in production, cost, and financial performance, particularly within the context of manufacturing enterprises.

## Methods and Materials

From the perspective of purpose, this research is applied. In terms of methodology, it is correlational, and regarding data collection, this study is descriptive–analytical, relying on library studies for information gathering. Descriptive research is used to examine existing conditions for better understanding, in order to assist the decision-making process.

The statistical population of this study is Mobarakeh Steel Company of Isfahan. Considering that the research data is quantitative, the data were extracted from existing documents and records. Consequently, the sample under study consists of data related to production performance, costs, and financial performance during the years 2016–2020. The sampling method in this research is purposive.

To collect information, both library and field methods were used. Library studies were employed as the foundation for developing the theoretical framework of the research, while the field method was utilized to obtain information directly from Mobarakeh Steel Company.

## Findings and Results

To account for potential conditions, sensitivity analysis was conducted on various variables. The results showed that the annual production plan and line inventory had the greatest impact on production planning. Based on these results, an appropriate hierarchical structure can be established to help improve production system performance.

**Scenario Analysis**

In this section, to examine the efficiency of the proposed algorithm and the effects of different variables on production system performance, several scenarios were created and analyzed. The purpose of scenario analysis is to simulate different production conditions and evaluate system performance under variable conditions. These scenarios assist managers in making more optimal decisions in real-world contexts.

**Scenario 1: Market Demand Increase**

In this scenario, market demand increases by 20%. The purpose is to assess the impact of increased demand on production planning and related costs.

*Scenario Assumptions:*

- 20% increase in order forecasts
- Other variables remain constant

**Table 1.**

*Results of Scenario 1*

| Variable | Change |
| --- | --- |
| Order forecast | +20% |
| Production costs | +15% |
| Monthly production | +18% |

These results indicate that increased market demand directly leads to higher production costs and monthly production volume.

**Scenario 2: Production Budget Reduction**

In this scenario, the production budget is reduced by 15%. The purpose is to assess the impact of budget reduction on production planning and production levels.

*Scenario Assumptions:*

- 15% reduction in production budget
- Other variables remain constant

**Table 2.**

*Results of Scenario 2*

| Variable | Change |
| --- | --- |
| Optimal warehouse level | -12% |
| Production costs | -10% |
| Monthly production | -15% |

These results indicate that a reduction in production budget leads to decreased monthly production levels and lower optimal warehouse capacity.

**Scenario 3: Production Optimization Considering Line Capacity**

In this scenario, production capacity of each line is increased by 10%. The purpose is to examine the effect of increased line capacity on production planning and related costs.

*Scenario Assumptions:*

- 10% increase in production line capacity
- Other variables remain constant

**Table 3.**

*Results of Scenario 3*

| Variable | Change |
| --- | --- |
| Line production capacity | +10% |
| Production costs | +5% |
| Monthly production | +8% |

These results indicate that increased production line capacity results in higher monthly production and a moderate increase in production costs.

**Scenario 4: Change in Inventory Policies**

In this scenario, the optimal level of each warehouse is increased by 20%. The purpose is to assess the impact of changes in inventory policies on production planning and related costs.

*Scenario Assumptions:*

- 20% increase in optimal warehouse level
- Other variables remain constant

**Table 4.**

*Results of Scenario 4*

| Variable | Change |
|---|---|
| Line production capacity | +20% |
| Production costs | +10% |
| Monthly production | +12% |

These results indicate that increasing optimal warehouse levels leads to higher inventory costs and an increase in monthly production volume.

Considering the results of the various scenarios, it can be observed that each variable has a significant impact on production system performance. For instance, increased market demand leads to higher production costs and monthly production, while reduced production budgets cause a decline in production levels and optimal warehouse capacity. These analyses help managers make more optimal decisions by taking different conditions into account, thereby improving production system performance.

The conducted scenario analysis demonstrates the practical applicability of the machine learning algorithm in hierarchical planning and enhancing production system performance. Using this approach, substantial improvements in production planning and management can be effectively achieved.

**Figure 1.**

*Impact of Different Scenarios on Monthly Production Levels*

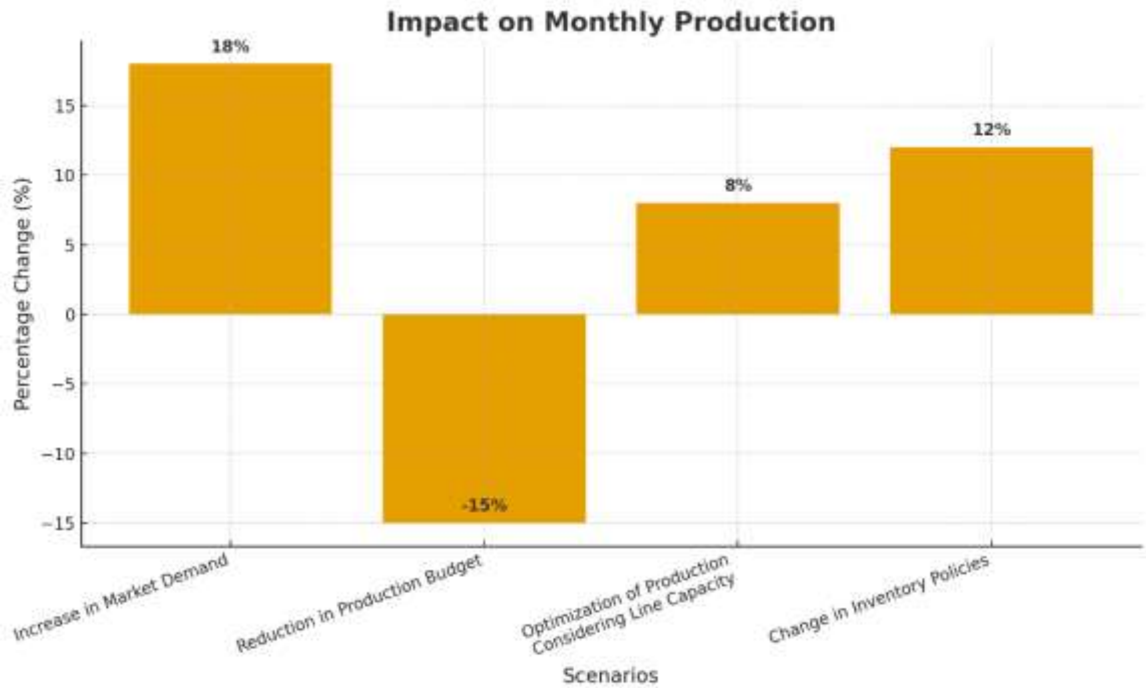


**Figure 2.**

*Effect of Budget and Policy Changes on Optimal Warehouse Capacity*

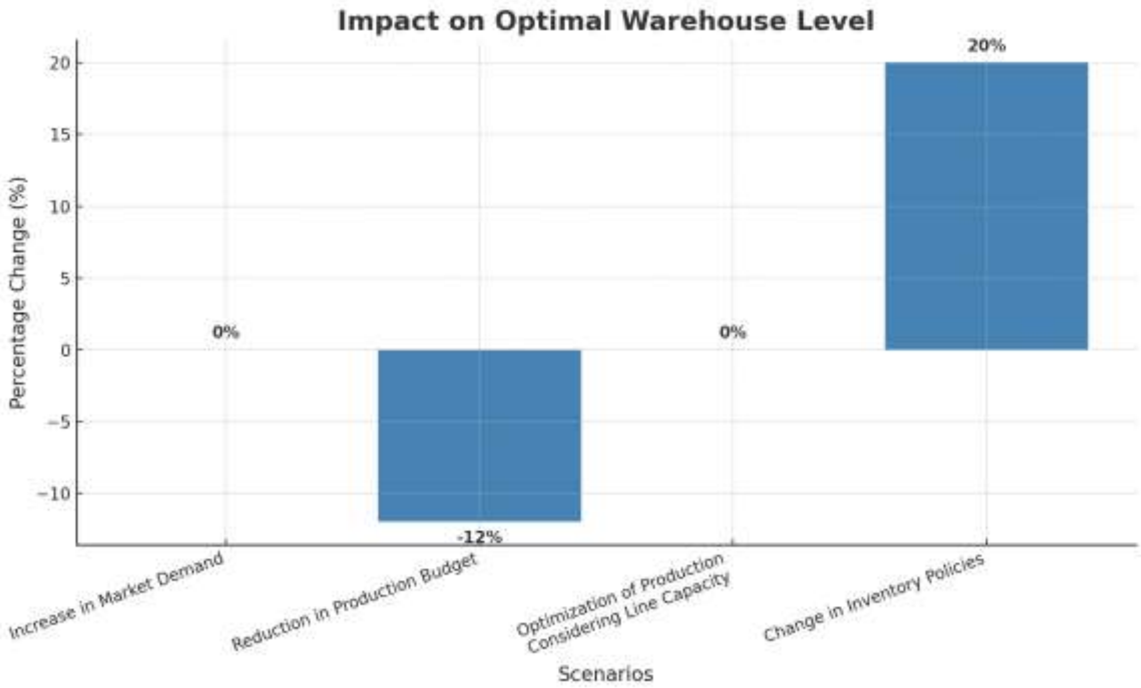
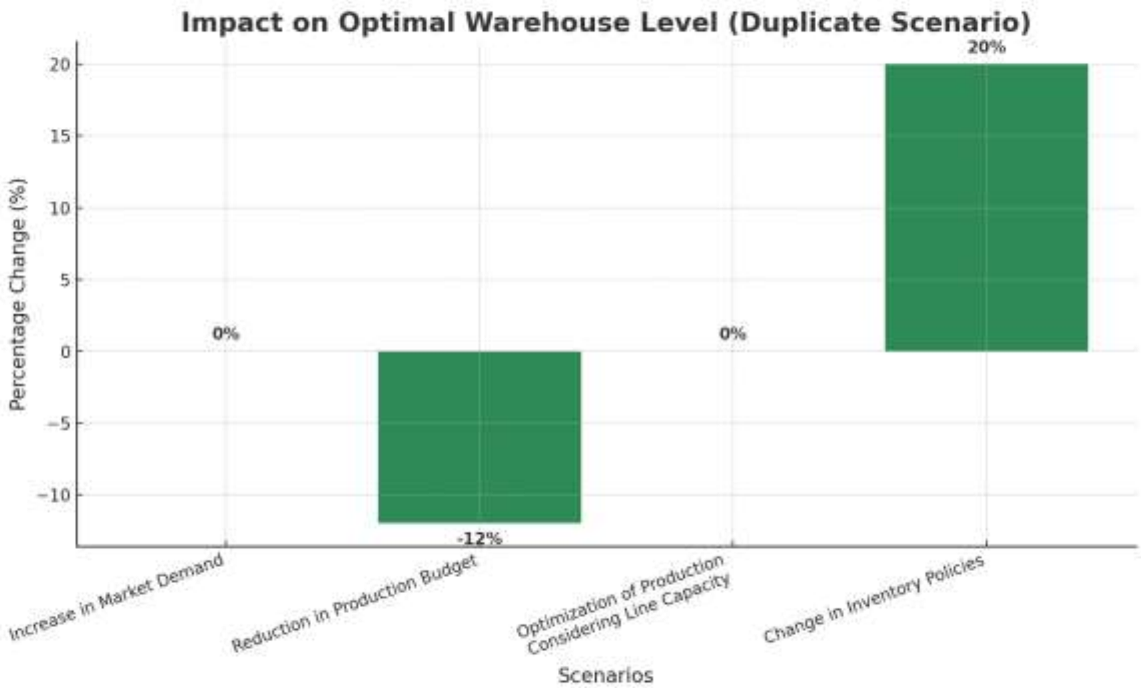



**Figure 3.**

*Comparative Scenario Analysis of Inventory Policy Adjustments on Warehouse Levels*




## Discussion and Conclusion

The findings of this study underscore the potential of machine learning (ML) in improving production planning, reducing costs, and enhancing financial performance in manufacturing enterprises. By employing the C4.5 decision tree algorithm, the research demonstrated that accurate predictions and scenario-based analyses can substantially improve hierarchical planning systems, aligning production with financial constraints and market dynamics. The results indicate that incorporating financial and operational data into ML models not only enhances prediction accuracy but also provides decision-makers with actionable insights into production scheduling, inventory optimization, and cost management.

The main outcome—that ML algorithms significantly improve the precision of production planning—echoes the broader literature on the transformative impact of ML in predictive modeling. For example, research on stock market forecasting shows that ML techniques can capture non-linear patterns and generate more reliable signals than traditional statistical models [7, 8]. Just as these models identify hidden structures in financial markets, the present study reveals that ML can identify subtle dependencies in production and cost data that support more accurate scheduling. This aligns with findings in risk management, where ML models such as ensemble learning and neural networks are preferred over linear methods for capturing dynamic interactions in financial variables [1, 13].

A key finding is that integrating financial constraints, such as raw material and production costs, into predictive models significantly affects production planning outcomes. This is consistent with prior research showing that financial indicators play a central role in predicting corporate failure and financial distress [11, 15]. By embedding cost variables in the ML framework, the model reflects real-world constraints, enabling more practical and feasible production strategies. In parallel, research on bankruptcy prediction using Shapley additive explanations demonstrates how combining financial and managerial features enhances the predictive validity of ML models [10]. The present study confirms that such multidimensional modeling strategies are not only applicable to financial markets but also extend effectively to production and cost optimization.

Furthermore, the accuracy rate of 85% obtained from the ML model provides robust evidence of the reliability of algorithm-driven production planning. This outcome resonates with earlier work in financial prediction, where high levels of accuracy in forecasting stock returns, startup financing methods, and risk-adjusted portfolios were achieved by integrating machine learning algorithms [2, 17]. The emphasis on accuracy as a proxy for managerial confidence is also supported by research showing that decision-makers rely more on predictive models when outputs are reliable, interpretable, and consistent with practical realities [10, 19].

The scenario analysis further enriches these findings by demonstrating how different external and internal conditions influence production and cost performance. Increases in market demand, for instance, were shown to raise both monthly production levels and costs, a result that parallels studies in financial markets where demand shocks lead to significant volatility and increased transaction costs [12]. Similarly, reductions in production budgets were found to lower both production capacity and inventory levels, consistent with evidence that financial constraints critically shape firm-level survival and resilience [5, 6]. The analysis of capacity increases and inventory policy shifts also highlights the adaptability of ML-driven planning systems, mirroring how adaptive ML models capture evolving patterns in volatile asset classes such as cryptocurrencies [2].

Collectively, the results of this study confirm that ML provides significant value in operational and financial domains by enabling managers to simulate scenarios, assess risks, and align production plans with financial realities. The evidence supports the growing consensus in literature that ML is not merely a supplementary tool but a strategic necessity for organizations navigating complexity [3, 4].

The alignment between the findings of this research and prior studies in finance and management highlights the interdisciplinary relevance of ML applications. The predictive performance of the C4.5 algorithm in production systems is comparable to that of ML models used in stock price forecasting, bankruptcy prediction, and credit risk analysis. For instance, Chen et al. [8] show how graphical signal recognition integrated with ML enhances financial market forecasting, while Nguyen et al. [10] demonstrate similar results in bankruptcy prediction. This reinforces the notion that ML models are versatile and transferable across different application domains.

The integration of financial costs into planning also mirrors findings in banking and credit evaluation, where ML has been applied to improve credit scoring accuracy and fairness [14, 15]. Just as ML provides more nuanced evaluations of borrower risk, in this study it delivered more realistic assessments of production plans under financial constraints. The evidence of improved managerial confidence in ML-driven outputs resonates with Singh and Kaunert [19], who argue that AI enhances trust in financial data security and decision systems when accuracy levels are demonstrably high.

The scenario analysis in this study builds on prior work in financial forecasting that uses ML to simulate the impact of market volatility and shocks. For example, Ghallabi et al. [12] employ ML to model how ESG and clean energy market fluctuations affect financial stability, while Song [2] applies similar techniques in cryptocurrency portfolio optimization. The methodological parallels suggest that scenario modeling through ML is a robust approach for testing system resilience, whether in financial markets or industrial production.

Moreover, the results contribute to discussions on the interpretability and transparency of ML. While many ML models achieve high accuracy, the lack of explainability often deters managerial adoption [10]. By employing a decision tree algorithm, this study addressed these concerns, providing interpretable and transparent predictions that managers could trust. This aligns with recent scholarship advocating for hybrid approaches that balance predictive accuracy with explainability [4, 9].

Finally, the study reinforces the importance of integrating behavioral and contextual variables into predictive models. Razavi [17] emphasizes that considering behavioral biases improves predictions of financing methods for startups, while this research highlights how incorporating financial constraints improves production planning accuracy. Together, these findings suggest that contextualized ML models are more effective than purely technical ones, pointing toward a future in which interdisciplinary models dominate both financial and managerial decision-making [16, 18].

## 1. Contributions to Literature and Practice

This study contributes to literature by extending the application of ML into the integrated domain of production, cost, and financial performance. While prior research has heavily emphasized financial forecasting, credit scoring, and bankruptcy prediction, fewer studies have systematically explored how ML can be applied to industrial production systems with embedded financial constraints [6, 15]. The results therefore provide empirical evidence that ML can serve as a bridge between operational efficiency and financial performance, offering new directions for both management scholars and practitioners.

Furthermore, the study validates the applicability of interpretable ML algorithms, such as decision trees, in environments where managerial trust and decision confidence are paramount. Unlike “black box” deep learning models that often lack transparency, decision tree-based algorithms present outputs that can be easily communicated and understood by managers, which is vital for implementation in practice [10, 19]. This highlights the practical dimension of ML adoption, underscoring the need to balance sophistication with usability.

Despite its contributions, this study has several limitations that must be acknowledged. First, the research is based on a single case study of Mobarakeh Steel Company, which may limit the generalizability of the findings to other industrial or financial contexts. The reliance on firm-specific data between 2016–2020 means that external shocks, such as global economic crises or supply chain disruptions, may not have been fully captured in the analysis. Second, the use of the C4.5 decision tree algorithm, while interpretable and accurate, may not fully exploit the predictive potential of more advanced ensemble or deep learning models, such as random forests, gradient boosting, or recurrent neural networks. Third, while financial constraints were incorporated into the model, other critical factors such as human resource management, energy costs, and environmental policies were excluded, potentially narrowing the scope of the predictions.

Future studies should extend the scope of this research by applying ML models to a wider range of firms across diverse industries, enabling cross-sectoral comparisons and enhancing generalizability. Incorporating advanced algorithms such as ensemble models, deep learning frameworks, and hybrid approaches may provide deeper insights and greater predictive power. Future research could also integrate behavioral, organizational, and environmental variables into the models, thereby reflecting the multidimensional complexity of production and financial systems. Another promising avenue is the use of explainable AI (XAI) methods, which would balance predictive accuracy with interpretability, addressing concerns of managerial trust and regulatory compliance. Finally, longitudinal studies that examine the adaptability of ML models under dynamic conditions such as economic crises, policy shifts, or technological disruptions would provide valuable insights into the resilience of algorithm-driven decision systems.

For practitioners, the findings highlight the importance of adopting ML as a strategic tool for production and financial planning. Managers should not view ML solely as a technical enhancement but as a holistic decision-support system capable of integrating financial, operational, and contextual data. Firms should prioritize interpretable models to build managerial confidence, particularly in industries where trust in decision systems is critical. Moreover, organizations should invest in developing managerial and technical expertise to effectively implement and maintain ML systems, ensuring alignment between technological potential and organizational readiness. Finally, scenario-based planning using ML can provide firms with a strategic advantage, enabling them to anticipate diverse conditions and respond with agility, thereby enhancing long-term competitiveness and resilience.

## Acknowledgments

We would like to express our appreciation and gratitude to all those who cooperated in carrying out this study.

## Authors' Contributions

All authors equally contributed to this study.

## Declaration of Interest

The authors of this article declared no conflict of interest.

## Ethical Considerations

The study protocol adhered to the principles outlined in the Helsinki Declaration, which provides guidelines for ethical research involving human participants. Written consent was obtained from all participants in the study.

## Transparency of Data

In accordance with the principles of transparency and open research, we declare that all data and materials used in this study are available upon request.

## Funding

This research was carried out independently with personal funding and without the financial support of any governmental or private institution or organization.

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