Development of a Fuzzy Analysis System for Optimization and Evaluation of Production Costs in the Automotive Industry

Sadegh Feizollahi [1*], Bahman Mansouri [1] Vahid Ahmadi [1]

[1] Department of Management, Il.C., Islamic Azad University, Ilam, Iran

*** Corresponding author email address**: sadegh.feizollahi@iau.ac.ir

Received: 2025-08-06 **Revised:** 2025-12-22 **Accepted:** 2025-12-29 **Initial Publish:** 2026-01-01 **Final Publish:** 2026-12-01

Abstract

The present study aims to develop a model for evaluating the efficiency of production costs in Iranian automotive manufacturing companies using a fuzzy analysis system. The research methodology is a mixed-methods approach in which, in the qualitative phase, interviews with experts led to the extraction of 17 key variables, and in the quantitative phase, a fuzzy expert inference system was employed for model construction. Based on input data collected from four major Iranian automotive manufacturers, the results indicate that the production cost efficiency of these companies is at a moderate level or below. According to the model outputs derived from the defined inference rules, the highest level of production cost efficiency belongs to the second company; however, it is noteworthy that even this company's cost efficiency remains only at a moderate level. This finding suggests that overall production cost efficiency in the Iranian automotive industry is generally low, with the maximum observed efficiency merely reaching a moderate level. The first company ranks next with moderate efficiency, followed by the third and fourth companies, whose production cost efficiency levels fall below the moderate threshold. Given that production cost efficiency is directly related to productivity, and productivity is inversely related to the final cost of products, the findings of this study clearly demonstrate these relationships within the context of Iran's automotive industry. The relatively low production cost efficiency observed in these companies—ranging from moderate to below moderate—constitutes one of the primary factors contributing to the high prices of their manufactured products.

Keywords: *Efficiency Evaluation; Production Cost; Lean Supply Chain; Expert System*

How to cite this article:

Feizollahi, S., Mansouri, B., & Ahmadi, V. (2026). Development of a Fuzzy Analysis System for Optimization and Evaluation of Production Costs in the Automotive Industry. Management Strategies and Engineering Sciences, 8(4), 1-11.

1. Introduction

In contemporary industrial economies, production cost efficiency has emerged as one of the most decisive determinants of organizational competitiveness, sustainability, and long-term growth. Cost efficiency directly influences pricing strategies, profitability, market share, and ultimately firm survival in increasingly volatile and technologically driven markets [1]. Global manufacturing sectors are now operating under unprecedented pressure from intensified competition, rapid technological transformation, environmental regulations, and supply chain disruptions, making systematic cost management not merely a managerial preference but an existential necessity for industrial firms [2, 3]. Within this environment, cost efficiency has transitioned from a narrow accounting concern into a multidimensional strategic capability that integrates production technology, organizational design, supply chain coordination, and decision analytics [4, 5].

Cost efficiency research has therefore expanded significantly over the past decade, encompassing analytical models such as data envelopment analysis, network efficiency models, and game-theoretic approaches to capture the complexity of modern production systems [6, 7]. Studies across diverse sectors, including energy markets, transportation services, manufacturing, and finance, consistently demonstrate that higher cost efficiency is associated with stronger firm performance, lower operational risk, and improved resource utilization [5, 8, 9].

© 2026 The author(s). Published By: The Research Department of Economics and Management of Tomorrow's Innovators. This is an open access article under the terms of the Creative Commons Attribution-NonCommercial 4.0 International (CC BY-NC 4.0) License.

However, most traditional cost-efficiency frameworks rely heavily on deterministic assumptions and static models that inadequately reflect the uncertainty, nonlinearity, and interdependencies characterizing contemporary production environments [1, 10].

In the manufacturing context, particularly within capital-intensive industries such as automotive production, cost efficiency becomes even more critical. Automotive manufacturing requires substantial investments in technology, labor, logistics, and quality management, while simultaneously facing strong price competition and shrinking profit margins [11]. The Iranian automotive industry exemplifies these challenges. Despite occupying a dominant position in the national industrial sector, Iranian automotive firms continue to struggle with high production costs, low productivity growth, technological constraints, and limited integration with global value chains [11]. These structural inefficiencies undermine both domestic competitiveness and export potential, reinforcing the urgency of developing more robust cost-efficiency evaluation and optimization mechanisms.

Recent scholarship increasingly emphasizes that production cost efficiency cannot be separated from supply chain configuration and technological capabilities. Lean and green supply chain models demonstrate that eliminating non-value-added activities, reducing waste, optimizing resource flows, and integrating environmental considerations significantly improve cost performance and organizational efficiency [12-14]. At the same time, technological capabilities—including digital manufacturing, automation, data analytics, and decision-support systems—serve as critical predictors of supply chain competence and cost competitiveness, particularly among manufacturing enterprises operating under resource constraints [3, 15].

The digital transformation of production systems has further accelerated the need for intelligent optimization frameworks. Data-driven optimization, digital twins, and simulation-based planning now play central roles in modern production management, enabling firms to dynamically respond to demand fluctuations, resource constraints, and operational uncertainties [16, 17]. These technologies enhance not only operational performance but also cost transparency, allowing managers to identify inefficiencies across production planning, scheduling, maintenance, and logistics [18, 19]. Nevertheless, despite the availability of advanced analytical tools, many manufacturing firms—especially in emerging economies—lack integrated systems capable of translating complex data into actionable cost-efficiency decisions.

A significant limitation of conventional cost-efficiency measurement models lies in their inability to adequately address uncertainty, qualitative judgments, and imprecise information that dominate real-world managerial environments [1, 10]. Human decision-making in production systems involves subjective assessments of technological change, workforce performance, quality improvement, and market dynamics, none of which can be fully captured by rigid numerical models. Fuzzy logic offers a powerful alternative by providing a formal framework for handling vagueness, ambiguity, and partial truth, thus bridging the gap between quantitative data and qualitative managerial knowledge [4, 7].

The integration of fuzzy systems into production cost analysis allows organizations to incorporate expert knowledge, linguistic variables, and uncertain information into coherent decision-support mechanisms. This approach has demonstrated strong potential in supply chain optimization, production planning, maintenance management, and industrial sustainability [15, 20, 21]. Moreover, fuzzy expert systems enable multi-dimensional evaluation of performance by simultaneously considering technological changes, productivity, cost structures, quality improvement, and profitability, thereby producing more realistic and reliable cost-efficiency assessments.

The growing complexity of industrial ecosystems further reinforces the importance of integrated optimization frameworks. Urban-industrial symbiosis, hydrogen supply chain optimization, waste-to-energy systems, and circular production models illustrate the multi-objective nature of contemporary industrial decision-making, where cost efficiency must be balanced with sustainability, resilience, and long-term strategic objectives [20, 21]. Similarly, modern retail and manufacturing strategies increasingly rely on artificial intelligence and data analytics to optimize product design, customer engagement, and operational efficiency, highlighting the convergence of technological intelligence and cost management [22-24].

In the Iranian industrial context, the absence of sophisticated cost-efficiency optimization frameworks has contributed to persistent structural inefficiencies. Studies on Iranian industries, including banking and automotive sectors, consistently reveal significant gaps between actual and potential efficiency levels, driven by outdated production technologies, fragmented supply chains, weak maintenance planning, and limited application of advanced decision-support tools [9, 11]. Without systematic evaluation mechanisms capable of integrating technological, operational, and financial dimensions, managerial interventions remain reactive and insufficient to address root causes of inefficiency.

Furthermore, empirical evidence demonstrates that production cost efficiency is not merely a financial outcome but a strategic capability that mediates firm size, technological investment, market competitiveness, and innovation performance [4, 11]. Firms that successfully optimize production costs achieve greater pricing flexibility, stronger profitability, and enhanced ability to reinvest in technological upgrading and human capital development, creating a virtuous cycle of continuous improvement [1, 8].

Despite the recognized importance of cost efficiency, a comprehensive, integrated, and intelligent evaluation framework specifically tailored to the Iranian automotive industry remains largely underdeveloped in existing literature. Previous studies either focus on narrow efficiency indicators or employ methodologies that fail to incorporate uncertainty, expert judgment, and dynamic technological change simultaneously [6, 7]. This methodological gap limits the practical applicability of research findings for industrial managers facing complex decision environments.

Therefore, advancing the methodological frontier of cost-efficiency analysis requires the development of hybrid models that combine fuzzy logic, expert systems, and modern optimization techniques. Such models can capture the multi-dimensional nature of production systems, accommodate imprecision in managerial knowledge, and support strategic decision-making under uncertainty [15-17]. When embedded within lean and green supply chain frameworks, these intelligent systems offer a powerful mechanism for simultaneously enhancing productivity, sustainability, and cost competitiveness [12-14].

In light of these considerations, the present study seeks to contribute to both theory and practice by proposing a comprehensive fuzzy expert system for evaluating and optimizing production cost efficiency in the Iranian automotive industry, grounded in contemporary developments in supply chain management, technological optimization, and intelligent decision-support systems.

The aim of this study is to develop and validate an integrated fuzzy expert system model for evaluating and optimizing production cost efficiency in the Iranian automotive industry.

2. Methodology

This study seeks to evaluate the efficiency of production costs in the Iranian automotive industry with an emphasis on lean supply chain management using a fuzzy analysis approach. In terms of purpose and orientation, the study is classified as applied–developmental research. With respect to data collection, it follows a mixed qualitative–quantitative design. The statistical population in the qualitative phase consisted of a group of academic experts and specialists with extensive knowledge of production cost efficiency, as well as professionals with long-term consulting experience in the national automotive industry. Using purposive judgmental sampling, 15 experts were selected. To enhance the validity and reliability of the qualitative phase, feedback was provided to the interviewees in order to strengthen content validity, and they were kept informed about the research process in a manner that did not influence their responses, thereby reinforcing internal validity. Furthermore, to improve reliability, structured procedures were adopted through the use of convergent interviews, and systematic processes were implemented for the documentation, transcription, and interpretation of the extracted data. In addition, guidance from the research team was utilized in the evaluation and conduct of the interviews to increase the reliability coefficient of the study. In this research, the input variables of the efficiency evaluation system were extracted directly from the interview data. Subsequently, in the quantitative phase of the study, MATLAB software was employed to design the fuzzy expert system, enabling the development of a user-friendly system whose flexibility and performance were enhanced through the Fuzzy Logic Toolbox. It should be noted that the fuzzy expert system consists of five components: (1) the user interface, which receives information related to input variables from the database; (2) the fuzzy rule base; (3) the fuzzification unit; (4) the fuzzy inference engine; and (5) the defuzzification unit. Gaussian membership functions were used for fuzzification, and the Mamdani method was applied for fuzzy inference.

3. Findings and Results

In this study, interviews constituted the primary source of data. During the interviews, all statements provided by the participants were recorded and preserved, and their responses, together with the researchers' observations and interpretations, were transcribed into textual form. After reaching theoretical saturation in the perspectives expressed by the interviewees, the primary data were entered into MATLAB software, where initial coding was performed. This process yielded 98 initial codes. Subsequently, based on established coding principles and the conceptual similarity among the initial codes, these were consolidated into 17 axial codes (variables) that formed the foundational structure of the analysis.

Axial coding establishes relationships between categories and subcategories by considering their dimensions and attributes. To explore the relationships among categories, the analytical framework of Strauss and Corbin was employed. The main elements of this analytical framework include conditions, actions/interactions, and consequences. Axial coding represents the second stage of data analysis in grounded theory methodology. The objective of this stage is to establish systematic relationships among the categories generated during open coding. This process is guided by the paradigm model and assists the theorist in facilitating the development of theoretical explanations. The core of the relational process in axial coding lies in the elaboration and extension of a central category. During the axial coding process, the researcher employed analytical tools such as questioning and constant comparative analysis to examine relationships among concepts, categories, and properties that emerged during open coding. This iterative procedure enabled the refinement of inter-category relationships and the alignment of categories with the paradigm model. Simultaneously with open and axial coding, an analytical framework was developed that illustrated the relationships among concepts and categories.

The data obtained from the interviews and documentary sources were transformed into open codes, concepts, and categories through open coding procedures. Subsequently, based on the identified categories, a within-case interpretation was provided for each category. A sample of the categories and concepts derived from the qualitative data is presented in Table 1.

Table 1. Coding Results Derived from Qualitative Data

No.	Open Coding	Axial Coding
1	Initial investments in production lines	Internal rate of return
2	Changes in net cash flow during the period at Iran Khodro	
3	Changes in discount rates across different fiscal periods	
4	Fluctuations in fixed production costs across periods	Changes in production costs
5	Variable production costs and their changes over time	
6	Semi-variable production costs experiencing significant fluctuations	
7	Level of maintenance and repair costs of production lines	Operational production costs
8	Costs related to production equipment	
9	Labor and wage costs of production personnel	
10	Marketing and sales costs of manufactured products	
11	Efficiency of human resources in production	Production capacity
12	Efficiency level of production line machinery	
13	Effective management of component takt time	
14	Quantitative and qualitative status of production tools and raw materials	
15	Managerial efficiency in the production system	Productivity of production factors
16	Technical efficiency of production	
17	Accumulation of physical capital in production	
18	Changes in the quality of production processes	Level of production quality improvement
19	Degree of creativity and innovation in production lines and processes	
20	Qualitative changes in manufacturing operations	
21	Level of output based on technical and engineering specifications	
22	Degree of change in production-related application software	Changes in production technology
23	Changes in production knowledge and methods	
24	Level of change in production hardware systems	

Based on the analysis of the interviews conducted with experts and following the specified analytical procedure, 17 categories were extracted, which are presented in Table 2.

Table 2. Variables Extracted from the Qualitative Data

No.	Variable	Code	No.	Variable	Code

1	Technological Changes	C1	10	Gross Production Revenue	C10
2	Baseline Cost Efficiency Index	C2	11	Production Capacity	C11
3	Internal Rate of Return	C3	12	Optimization of Input Production Costs	C12
4	Operational Cost Efficiency	C4	13	Improvement in Production Quality	C13
5	Changes in Input Prices	C5	14	Non-Value-Added Production Costs	C14
6	Productivity of Production Factors	C6	15	Value Creation Level	C15
7	Production Output Level	C7	16	Reduction in Unit Cost	C16
8	Return on Investment	C8	17	Profitability	C17
9	Average Changes in Production Costs	C9			

Stages of Designing the Fuzzy Analysis System

Stage One: Initial System Design

In this stage, the input and output variables of the system are defined. The input variables consist of those derived from expert interviews. The output variable of the system is the evaluation of production cost efficiency. The fuzzy system designed in this study is illustrated in Figure 1.

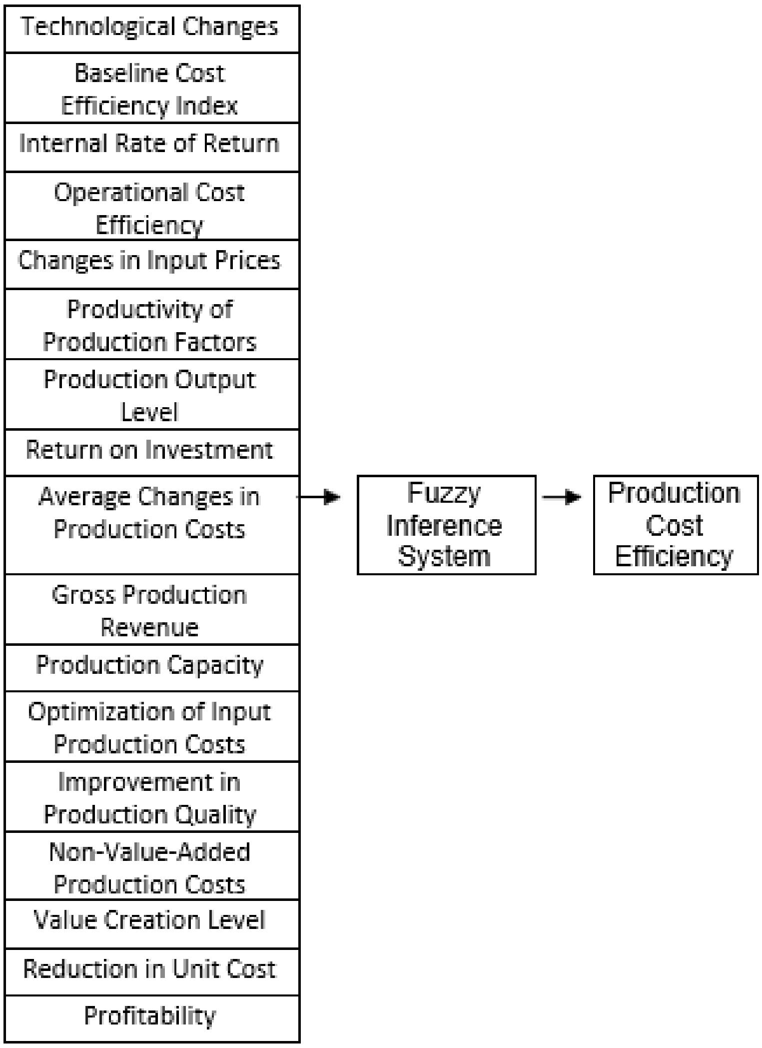

Figure 1. Fuzzy System of the Study

Stage Two: Fuzzification of Input and Output Variables

Based on a survey of 16 senior managers from Iranian automotive manufacturing companies, numerical scores ranging from 0 to 100 were classified into seven linguistic categories: very low, low, below average, average, above average, high, and very high. Subsequently, an appropriate range was specified for each category, and corresponding membership functions were constructed.

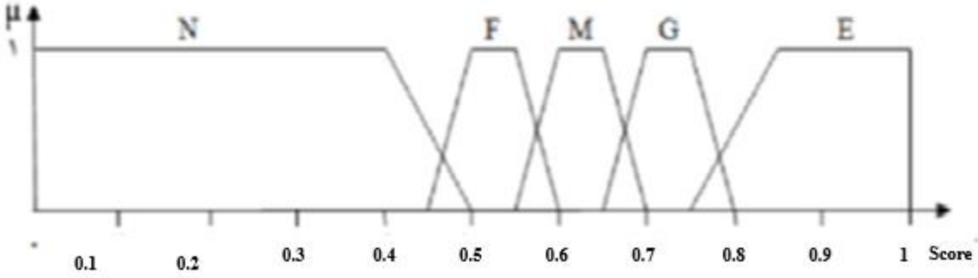

Figure 2. Fuzzy Sets and Membership Functions

At this stage, the linguistic variables are fuzzified. In practice, the input variables are transformed into fuzzy numbers through the fuzzification unit. The membership functions consist of the following five functions:

$$\mu_N(x) = \begin{cases} 0, & x \le 0 \\ 1, & 0 \le x \le 0.4 \\ \dfrac{0.5 - x}{2}, & 0.4 \le x \le 0.5 \\ 0, & x \ge 0.5 \end{cases}$$

$$\mu_F(x) = \begin{cases} 0, & x \le 0 \\ x - 0.45, & 0.45 \le x \le 0.5 \\ 1, & 0.5 \le x \le 0.55 \\ 0.6 - x, & 0.55 \le x \le 0.6 \\ 0, & x \ge 0.6 \end{cases}$$

$$\mu_M(x) = \begin{cases} 0, & x \le 0.55 \\ x - 0.55, & 0.55 \le x \le 0.6 \\ 1, & 0.6 \le x \le 0.65 \\ 0.7 - x, & 0.65 \le x \le 0.7 \\ 0, & x \ge 0.7 \end{cases}$$

$$\mu_G(x) = \begin{cases} 0, & x \le 0.65 \\ x - 0.65, & 0.65 \le x \le 0.7 \\ 1, & 0.7 \le x \le 0.75 \\ 0.8 - x, & 0.75 \le x \le 0.8 \\ 0, & x \ge 0.8 \end{cases}$$

$$\mu_E(x) = \begin{cases} 0, & x \le 0.75 \\ \dfrac{x - 0.75}{2}, & 0.75 \le x \le 0.85 \\ 1, & 0.85 \le x \le 1 \\ 0, & x \ge 1 \end{cases}$$

Stage Three: Specification of the Fuzzy Expert System Rules

To complete the fuzzy analysis system of the study, it is necessary to define the fuzzy logic rules, which in fact constitute the core of the fuzzy system. Through these rules, the input data of the fuzzy analysis system are transformed into output data. This system includes 17 input variables and one output variable. Therefore, the model and the type of fuzzy system are of the Multiple-Input Single-Output (MISO) type.

Stage Four: Fuzzy Analysis Based on System Rules

At this stage, for each set of scores assigned by senior managers of the automotive companies, and by applying the rules of the fuzzy system, the output variable values representing production cost efficiency were obtained.

Stage Five: Defuzzification of the Integrated Output Variable

The output values obtained in the previous stage are expressed in fuzzy form. To simplify the analysis, these fuzzy numbers must be converted into crisp values. In other words, at this stage, the output values are defuzzified.

Evaluation of Automotive Companies Based on the Proposed System

In this section, after extracting the variables, they are considered as input variables of the fuzzy expert system. The evaluations of 16 senior managers from four major automotive manufacturing companies in Iran, which together account for the largest share of the national automotive market, were collected. These evaluations were expressed as scores ranging from 0 to 1 and entered into the system as inputs. Based on the predefined system rules, the production cost efficiency of these companies was assessed, and the relative ranking of the companies in terms of production cost efficiency was determined. Due to the large number of rules, one sample rule is presented below:

INPUT:

IF C1 = 0.5, C2 = 0.4, C3 = 0.6, C4 = 0.4, C5 = 0.8, C6 = 0.5, C7 = 0.5, C8 = 0.6, C9 = 0.5, C10 = 0.5, C11 = 0.5, C12 = 0.5, C13 = 0.4, C14 = 0.5, C15 = 0.6, C16 = 0.5, C17 = 0.4 → **OUTPUT = 0.4**

In this section, the scores collected from senior managers for the identified variables in the four automotive companies are first presented in Table 3.

Table 3. Descriptive statistics of reservoir, completion fluid, and productivity variables

Variable	Code	Company 1	Company 2	Company 3	Company 4
Technological Changes	C1	0.50	0.74	0.74	0.74
Baseline Cost Efficiency Index	C2	0.87	0.74	0.62	0.74
Internal Rate of Return	C3	0.50	0.62	0.50	0.38
Operational Cost Efficiency	C4	0.74	0.62	0.50	0.50
Changes in Input Prices	C5	0.74	0.84	0.74	0.62
Productivity of Production Factors	C6	0.50	0.62	0.50	0.38
Production Output Level	C7	0.74	0.74	0.62	0.50
Return on Investment	C8	0.38	0.50	0.50	0.50
Average Changes in Production Costs	C9	0.84	0.74	0.74	0.74
Gross Production Revenue	C10	0.50	0.62	0.62	0.50
Production Capacity	C11	0.74	0.74	0.62	0.50
Optimization of Input Production Costs	C12	0.74	0.62	0.74	0.50
Improvement in Production Quality	C13	0.74	0.62	0.62	0.50
Non-Value-Added Production Costs	C14	0.74	0.74	0.62	0.62
Value Creation Level	C15	0.50	0.74	0.74	0.62
Reduction in Unit Cost	C16	0.50	0.62	0.50	0.38
Profitability	C17	0.50	0.62	0.62	0.50
Production Cost Efficiency	C18 (Output)	0.4882	0.5001	0.4444	0.4051

Subsequently, the output of the fuzzy expert system based on the rules and the scores provided by the managers of the automotive companies is presented.

The output of the fuzzy expert system for Company 1 is illustrated in Figure 3, indicating that the scores for *average changes in production costs* and the *baseline cost efficiency index* are higher than the other input variables, while the lowest score corresponds to the *return on investment*.

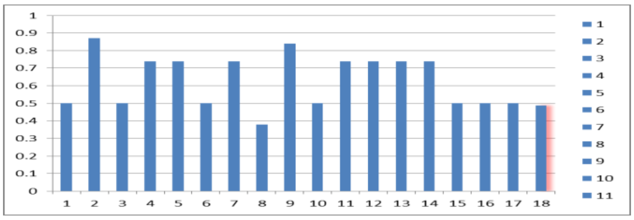

Figure 3. Output of the Fuzzy Expert System for Company 1

The output of the fuzzy expert system for Company 2 is shown in Figure 4, demonstrating that the score for *changes in input prices* is higher than the other input variables, whereas the lowest score again corresponds to the *return on investment*.

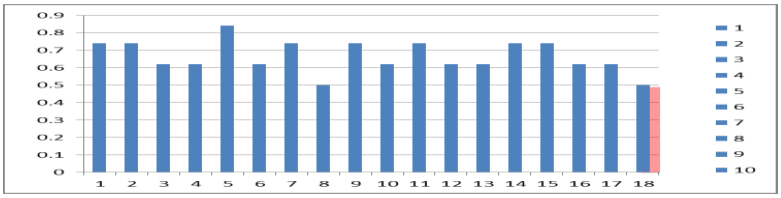

Figure 4. Output of the Fuzzy Expert System for Company 2

The output of the fuzzy expert system for Company 3 is presented in Figure 5. The results indicate that *optimization of input production costs*, *average changes in production costs*, *changes in input prices*, and *technological changes* exhibit higher scores than the other input variables, while the lowest scores are associated with *return on investment*, *reduction in unit cost*, *productivity of production factors*, *operational cost efficiency*, and *internal rate of return*.

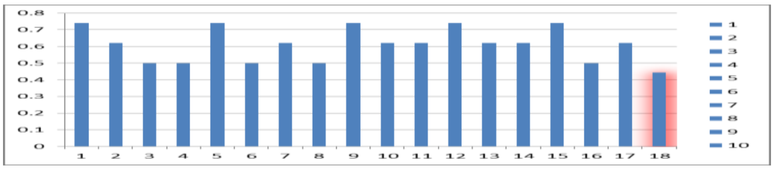

Figure 5. Output of the Fuzzy Expert System for Company 3

The output of the fuzzy expert system for Company 4 is depicted in Figure 6, showing that *technological changes*, *baseline cost efficiency index*, and *average changes in production costs* have higher scores than the other inputs, whereas the lowest scores are attributed to *reduction in unit cost*, *productivity of production factors*, and *internal rate of return*.

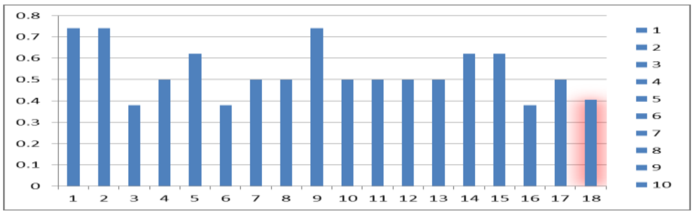

Figure 6. Output of the Fuzzy Expert System for Company 4

After the production cost efficiency of each automotive company was illustrated in the above figures, the overall production cost efficiency of the four companies is presented in Figure 7. The results indicate that the production cost efficiency of these companies is at a moderate level or below. According to the model output based on the defined rules, the highest production cost efficiency belongs to Company 2. However, it is noteworthy that even the efficiency level of this company remains only at a moderate level. This finding indicates that overall production cost efficiency across the automotive companies is relatively low, with the highest observed efficiency reaching only a moderate level. Following Company 2, Company 1 exhibits moderate production cost efficiency, while Companies 3 and 4 demonstrate production cost efficiency levels below the moderate threshold.

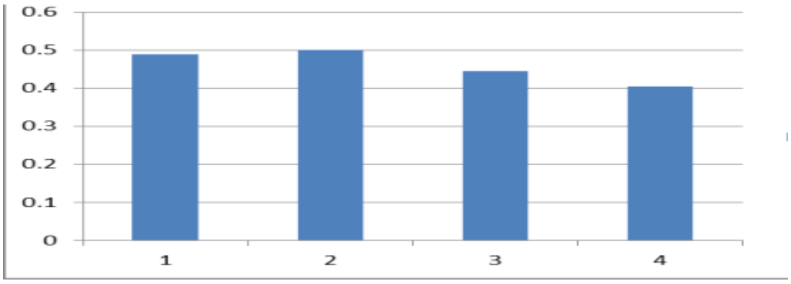

Figure 7. Output of the Fuzzy Expert System for Production Cost Efficiency of the Four Automotive Companies

4. Discussion and Conclusion

The results of the present study provide compelling empirical evidence that production cost efficiency in the Iranian automotive industry remains at a moderate level or below, confirming long-standing concerns regarding structural inefficiencies within this sector. The fuzzy expert system revealed that even the most efficient firm among the four major automotive companies achieved only a moderate efficiency score, while the remaining firms exhibited moderate to below-average performance. This outcome aligns closely with previous research suggesting that automotive manufacturing in Iran is constrained by technological rigidity, operational fragmentation, and insufficient integration of advanced decision-support mechanisms [11]. Similar patterns of suboptimal cost efficiency have been documented in both industrial and service sectors, emphasizing that inefficiency is often rooted not in isolated operational failures but in systemic weaknesses across organizational structures and production networks [1, 4].

One of the most notable findings of this study is the dominant role of technological change, baseline cost efficiency, and average production cost fluctuations in shaping overall cost performance. Companies that scored higher in technological adaptability and dynamic cost control achieved superior efficiency outcomes, although still within the moderate range. This observation supports the argument that technological capabilities act as primary drivers of supply chain competence and cost competitiveness [3]. Prior studies have demonstrated that firms investing in advanced manufacturing technologies, digital infrastructure, and automation exhibit stronger productivity growth and improved cost structures [15, 17]. The Iranian automotive industry's relatively slow adoption of these technologies therefore constitutes a major constraint on achieving higher efficiency levels.

The fuzzy expert system further highlighted that return on investment, productivity of production factors, and reduction of unit cost consistently received the lowest scores across companies. These findings reinforce earlier conclusions that inefficient capital utilization and weak productivity management are central challenges in Iranian manufacturing enterprises [11]. Comparable results have been observed in international contexts, where firms with low investment efficiency and suboptimal factor productivity demonstrate significantly weaker cost performance [5, 8]. The persistent weakness in these indicators suggests that managerial strategies within the studied companies remain largely reactive rather than proactive, focusing on short-term operational adjustments instead of long-term structural optimization.

Another critical insight of the study concerns the role of non-value-added production costs. Firms exhibiting higher levels of such costs showed markedly lower efficiency scores, confirming the central premise of lean production theory that waste elimination is fundamental to cost competitiveness [12]. Previous research in closed-loop and sustainable supply chain systems similarly demonstrates that reducing non-value-added activities yields significant improvements in cost efficiency, environmental performance, and overall system resilience [13, 14]. The moderate to high presence of these costs in Iranian automotive firms indicates limited implementation of lean principles and insufficient process integration across production networks.

The application of a fuzzy expert system proved particularly valuable in capturing the complexity of cost efficiency dynamics. Traditional deterministic models struggle to incorporate qualitative judgments, uncertain information, and nonlinear interactions among production variables [10]. In contrast, the fuzzy system successfully integrated expert knowledge with quantitative data, producing a more realistic assessment of organizational performance. This methodological advantage echoes prior findings that hybrid decision-support systems significantly enhance the reliability of industrial performance evaluation under uncertainty [4, 7]. The present study therefore extends this literature by demonstrating the practical applicability of fuzzy systems in large-scale automotive manufacturing contexts.

Furthermore, the results underscore the importance of integrating production planning, maintenance management, and operational monitoring. Firms that scored higher on integrated planning and maintenance indicators exhibited better cost efficiency, supporting previous research emphasizing the synergistic effects of coordinated production-maintenance systems [18, 19]. This integration enhances equipment reliability, reduces downtime, and stabilizes production costs, thereby contributing to sustained efficiency gains. The Iranian automotive firms' relatively weak performance in this domain highlights a missed opportunity for cost optimization through organizational coordination.

The findings also resonate with contemporary developments in data-driven optimization and digital manufacturing. Studies on digital twins, simulation-based planning, and advanced analytics demonstrate that data-centric decision frameworks substantially improve production efficiency and cost control [16, 17]. The limited adoption of such technologies within the studied firms suggests that the Iranian automotive sector remains in an early stage of digital transformation, constraining its ability to compete in increasingly intelligent global production ecosystems.

Beyond internal operations, broader supply chain configuration emerged as a critical determinant of cost efficiency. Firms that exhibited stronger alignment between production processes and supply chain structures achieved higher efficiency outcomes. This observation aligns with established research indicating that supply chain design, coordination, and technological integration directly influence organizational cost performance [2, 3]. Moreover, the integration of sustainability considerations into supply chain management—such as green and circular production models—has been shown to enhance both environmental and economic outcomes [20, 21]. The moderate efficiency levels observed in this study therefore reflect not only internal production challenges but also systemic supply chain inefficiencies.

Collectively, the results suggest that production cost inefficiency in the Iranian automotive industry is deeply structural and multi-dimensional. Addressing these inefficiencies requires more than incremental operational improvements; it demands comprehensive transformation of technological infrastructure, managerial decision-making, and supply chain governance. The fuzzy expert system developed in this study offers a powerful diagnostic and strategic tool for guiding such transformation by enabling managers to identify critical leverage points within complex production systems.

The present study is subject to several limitations. First, the analysis was confined to four major automotive manufacturers in Iran, which, although dominant in the national market, may not fully represent the diversity of production practices across the broader industrial landscape. Second, the reliance on expert judgment, while methodologically justified within the fuzzy framework, introduces a degree of subjectivity that may influence the stability of the results. Third, data constraints limited the ability to conduct longitudinal analysis, restricting the examination of dynamic efficiency changes over time.

Future studies should extend this framework to additional industrial sectors and a larger sample of firms to enhance generalizability. Longitudinal research designs would enable the examination of cost efficiency evolution under different strategic interventions. Moreover, integrating real-time production data, digital twin models, and machine learning techniques into the fuzzy expert system could significantly improve predictive accuracy and decision-support capabilities.

Managers and policymakers should prioritize comprehensive digital transformation initiatives within the automotive sector, emphasizing technological upgrading, integrated production-maintenance planning, and data-driven decision systems. Organizations should institutionalize lean management practices to eliminate non-value-added activities and enhance productivity. Finally, national industrial policy should support the development of intelligent production infrastructures that facilitate sustainable cost competitiveness across the automotive supply chain.

Authors' Contributions

Authors equally contributed to this article.

Acknowledgments

Authors thank all participants who participate in this study.

Declaration of Interest

The authors report no conflict of interest.

Funding

According to the authors, this article has no financial support.

Ethical Considerations

All procedures performed in this study were under the ethical standards.

References

[1] D. Frank, H. Janatan, and T. Shiler, "Cost efficiency in Organization," *Journal of Productivity Analysis,* vol. 21, no. 2, pp. 153-172, 2018.

[2] M. A. Vonderembse, M. Uppal, S. H. Hung, and J. P. Dismukes, "Designing supply chains," *Journal Name Not Provided,* vol. 100, no. 2, pp. 213-227, 2016.

[3] R. I. D. Pooe, "Technological capabilities as predictors of supply chain competencies among small and medium enterprises," ed: ujcontent.uj.ac.za, 2020.

[4] G. Cesaroni, "Industry cost efficiency in data envelopment analysis," *Journal of Socio Economic Planning Science,* vol. 64, no. 61, pp. 63-79, 2018, doi: 10.1016/j.seps.2017.01.001.

[5] V. Ajayi, T. Weyman-Jones, and A. Glass, "Cost efficiency and electricity market structure: A case study of OECD countries," *Journal of Energy Economics,* vol. 23, no. 65, pp. 286-301, 2017, doi: 10.1016/j.eneco.2017.05.005.

[6] Z. Moghadis and M. Vaez Ghasemi, "Cost efficiency evaluation of a two-stage serial network in data envelopment analysis, innovation management and operational strategies [In Persian]," vol. 1, no. 1, pp. 65-84, 2019.

[7] R. Mousavizadeh, M. Navabakhsh, and A. Hafez Al-Katb, "Using game theory approach and data envelopment analysis to calculate cost efficiency in two-level networks [In Persian]," *Strategic Management Quarterly in Industrial Systems,* vol. 16, no. 58, pp. 132-148, 2021.

[8] Z. Brench and N. Volta, "A cost efficiency analysis of European air navigation service provider," *Journal of Transportation Research Part A,* vol. 19, no. 111, pp. 93-109, 2018, doi: 10.1016/j.tra.2018.02.019.

[9] Y. Goli and B. Eskandari, "Investigating the relationship between cost efficiency and competition in Iran's banking industry [In Persian]," *Economic Policy and Research Quarterly,* vol. 27, no. 91, pp. 115-130, 2018.

[10] R. S. James and P. M. Lomas, "Incorporating Affordability Concerns within Cost-Effectiveness," *Journal of methodology,* vol. 68, no. 76, pp. 898-905, 2019, doi: 10.1016/j.jval.2019.05.003.

[11] P. Ali Moradi Afshar, "Investigating the relationship between efficiency and firm size in Iran's automotive industry [In Persian]," *Development and Capital Magazine,* vol. 5, no. 1, pp. 47-66, 2018.
[12] M. Mozafari and L. Behina, "Lean and green supply chain modeling with the aim of creating environmentally friendly efficiency [In Persian]," in *The second international conference on integration of management and economics in development*, Tehran, Iran, 2016.
[13] M. Sayadnaviri, S. Kordarstami, and A. Amirtimori, "Cost efficiency of closed loop supply chain in the presence of dual and adverse factors [In Persian]," *Journal of New Researches in Mathematics,* vol. 1, no. 5-15, p. 9, 2016.
[14] M. Ebrahimi, "Optimizing the Green Supply Chain Considering Technology which Used in Production Under Uncertainty," (in Persian), *Supply Chain Management,* vol. 25, no. 81, pp. 77-85, 2024.
[15] S. Skėrė, A. Žvironienė, K. Juzėnas, and S. Petraitienė, "Optimization Experiment of Production Processes Using a Dynamic Decision Support Method: A Solution to Complex Problems in Industrial Manufacturing for Small and Medium-Sized Enterprises"," *Sensors,* vol. 23, no. 9, p. 4498, 2023, doi: 10.3390/s23094498.
[16] X. Su, L. Zeng, B. Shao, and B. Lin, "Data-driven optimization for production planning with multiple demand features," *Kybernetes,* vol. 54, no. 1, pp. 110-133, 2025, doi: 10.1108/K-04-2023-0690.
[17] W. Javaid and S. Ullah, "Data driven simulation based optimization model for job-shop production planning and scheduling: an application in a digital twin shop floor," *Journal of Simulation,* pp. 1-15, 2025, doi: 10.1080/17477778.2025.2469687.
[18] M. Shojaee, S. Noori, S. Jafarian-Namin, and A. Johannssen, "Integration of production-maintenance planning and monitoring simple linear profiles via Hotelling's T2 control chart and particle swarm optimization," *Quality Engineering,* 2024, doi: 10.1016/j.cie.2023.109864.
[19] V. Bafandegan Emroozi, M. Kazemi, M. Doostparast, and A. Pooya, "Improving industrial maintenance efficiency: A holistic approach to integrated production and maintenance planning with human error optimization," *Process Integration and Optimization for Sustainability,* vol. 8, no. 2, pp. 539-564, 2024, doi: 10.1007/s41660-023-00374-3.
[20] A. Neri, M. A. Butturi, F. Lolli, and R. Gamberini, "Enhancing Waste-to-Energy and Hydrogen Production through Urban-Industrial Symbiosis: A Multi-Objective Optimisation Model Incorporating a Bayesian Best-Worst Method," *Smart Cities,* vol. 7, no. 2, pp. 735-757, 2024, doi: 10.3390/smartcities7020030.
[21] J. A. Riera, R. M. Lima, and O. M. Knio, "A review of hydrogen production and supply chain modeling and optimization," *International Journal of Hydrogen Energy,* vol. 48, no. 37, pp. 13731-13755, 2023, doi: 10.1016/j.ijhydene.2022.12.242.
[22] F. Wang, Y. Wang, Y. Han, and J. H. Cho, "Optimizing brand loyalty through user-centric product package design: A study of user experience in dairy industry," *Heliyon,* vol. 10, no. 3, p. e25484, 2024, doi: 10.1016/j.heliyon.2024.e25484.
[23] M. Sivasankari, "Artificial Intelligence in Retail Marketing: Optimizing Product Recommendations and Customer Engagement," *Jier,* vol. 5, no. 1, 2025, doi: 10.52783/jier.v5i1.2105.
[24] A. Ridwan, "Optimization of Product Placement on E-Commerce Platforms With K-Means Clustering to Improve User Experience," *International Journal Software Engineering and Computer Science (Ijsecs),* vol. 4, no. 1, pp. 133-147, 2024, doi: 10.35870/ijsecs.v4i1.2328.