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Identification and Leveling of Production Technology Selection Indicators in Iran's Steel Industry Using Qualitative Content Analysis

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ABSTRACT

The main objective of the present study was to identify and level the indicators for selecting production technology in Iran's steel industry using qualitative content analysis. The first step of the research was related to identifying production technology selection indicators in industries, and the statistical population included articles related to the identification of production technology selection indicators in industries. The population size was 124 articles, and the sample size was considered to be 71 articles. The sampling method in this section was judgmental sampling. The second to fourth steps of the research addressed the localization, analysis of influencing and influenced relationships, and leveling of production technology selection indicators in Iran's steel industry. The statistical population in this section included academic scholars and industry experts who were knowledgeable about production technology selection indicators in Iran's steel industry. The sample size in this section was determined to be 12 experts. The sampling method in this stage was purposive sampling. The data collection method and instrument in the first step consisted of a library-based study. The data collection instrument in this section involved note-taking and extraction from various articles and books related to the subject. The data collection method in the second, third, and fourth steps was field-based, and the data collection instrument in these steps was a questionnaire. The data analysis method in the first step was the qualitative content analysis approach. In qualitative content analysis, efforts are made to identify and extract content categories present in communication messages through open coding, axial coding, and selective coding. Ultimately, by entering the codes into specialized NVivo software, the indicators were screened and finalized through an agreed-upon coding process. In the second step, the Delphi method was used to localize production technology selection indicators in Iran's steel industry. In the third step, in order to examine the influencing and influenced relationships among production technology selection indicators in Iran's steel industry, cross-impact analysis was conducted using MICMAC analysis for structural analysis in futures studies. To identify important and key components, both the Direct Method and the Indirect Method were applied. In the fourth step, Interpretive Structural Modeling (ISM) was used to level the production technology selection indicators in Iran's steel industry. Based on the results, the production technology selection indicators in Iran's steel industry—including technical and operational risk, production flexibility, digitalization capability and intelligentization through artificial intelligence, product quality, operating cost, availability and sustainability of feedstock, price acceptability and volatility of inputs, and supply chain security of equipment—were identified at Level 1 and recognized as the most influenced indicators in the selection of production technology in Iran's steel industry.

Keywords: Production technology, steel industry, content analysis.

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Introduction

The steel industry is widely recognized as one of the most critical pillars of industrial development, serving as a foundational sector that supports infrastructure construction, transportation, energy systems, and manufacturing activities worldwide. Steel production technologies have evolved significantly over the past decades, transitioning from conventional, resource-intensive methods toward more efficient, environmentally sustainable, and digitally integrated production systems. This transformation is driven by increasing global competition, environmental regulations, and technological innovation, which collectively necessitate careful and strategic technology selection decisions within steel manufacturing enterprises. The selection of appropriate production technology is not merely a technical decision but a multidimensional strategic process that affects operational efficiency, environmental performance, economic viability, and long-term competitiveness. As modern steel production systems become more technologically sophisticated, selecting optimal production technologies has become a decisive factor influencing industrial sustainability and competitive advantage in global markets (1, 2).

Technological innovation has played a transformative role in reshaping steel production processes by improving productivity, enhancing product quality, and reducing environmental impacts. Recent advancements such as clean short-process steelmaking, carbon capture technologies, and digitalized production systems have demonstrated the potential to significantly reduce energy consumption and greenhouse gas emissions while improving production efficiency. For example, innovative short-process production technologies centered on high-purity iron concentrate have enabled cleaner steel production by reducing reliance on traditional blast furnace methods and improving overall process efficiency (3). Similarly, emerging carbon capture technologies such as DMX™ systems have shown substantial potential in mitigating carbon emissions in steel manufacturing, reinforcing the importance of selecting environmentally sustainable production technologies in alignment with global climate goals (4). These developments highlight that production technology selection is increasingly influenced by environmental sustainability considerations alongside traditional performance metrics such as cost, productivity, and reliability.

In addition to environmental considerations, digital transformation has introduced new dimensions into technology selection processes. Digital technologies, including artificial intelligence, automation, and digital information systems, have enhanced decision-making capabilities, process optimization, and production monitoring. Digital information selection mechanisms have demonstrated significant influence on the adoption of ecological production technologies by enabling better information accessibility, improving decision quality, and facilitating technological integration across production systems (5). The integration of digital technologies into steel manufacturing not only improves operational efficiency but also enhances flexibility, predictive maintenance capabilities, and supply chain coordination. Consequently, digitalization has become a key criterion in evaluating and selecting production technologies within modern steel industries.

The increasing complexity of industrial systems has further emphasized the importance of structured and systematic technology selection frameworks. Technology selection involves evaluating multiple criteria, including technical performance, economic feasibility, environmental impact, operational flexibility, and technological readiness. Multi-criteria decision-making models have been widely applied to support technology selection decisions by integrating quantitative and qualitative criteria into structured analytical frameworks. Studies applying fuzzy TOPSIS, AHP, and other decision-making models have demonstrated their effectiveness in identifying optimal production technologies by considering diverse performance indicators and uncertainty factors (6, 7). These approaches enable decision-makers to evaluate competing technologies comprehensively and objectively, reducing decision uncertainty and enhancing strategic planning capabilities.

The importance of technology selection extends beyond steel production and has been recognized across various industrial sectors. In manufacturing and production industries, the selection of production technologies is influenced by raw material properties, production methods, and technological capabilities. The relationship between raw materials and production technology has been shown to significantly affect product quality, operational efficiency, and production outcomes, highlighting the need for careful technology selection aligned with production requirements (8). Similarly, studies in industrial engineering and process optimization have demonstrated that selecting appropriate technological schemes can significantly improve operational performance, safety, and efficiency in complex industrial environments (9). These findings underscore the universal importance of technology selection as a strategic process influencing industrial productivity and competitiveness.

Environmental sustainability has emerged as one of the most influential drivers of technology selection in steel manufacturing. Governments and regulatory bodies worldwide have implemented stringent environmental regulations to reduce carbon emissions, improve energy efficiency, and promote sustainable production practices. Policy incentives and regulatory frameworks have significantly influenced technology selection decisions by encouraging the adoption of low-carbon and environmentally friendly production technologies. Studies examining carbon neutrality pathways in the steel industry have demonstrated that selecting appropriate technological pathways is essential for achieving long-term sustainability and regulatory compliance (10). Furthermore, green innovation initiatives such as FINEX technology have illustrated how technological innovation systems can accelerate the development and adoption of environmentally sustainable steel production technologies (1). These developments reinforce the importance of incorporating environmental performance indicators into technology selection frameworks.

Economic competitiveness remains a central factor influencing technology selection decisions in steel production. Production technologies directly affect operational costs, capital investment requirements, productivity levels, and return on investment. The competitiveness of steel manufacturing firms depends largely on their ability to adopt efficient production technologies that minimize production costs while maintaining product quality and operational reliability. Research on steel industry competitiveness models has highlighted the critical role of technology transfer, technological innovation, and production efficiency in enhancing industrial competitiveness and economic performance (11). Additionally, improvements in steel production technologies have demonstrated significant potential to enhance production efficiency, reduce operational risks, and improve infrastructure performance in industrial applications such as pipeline manufacturing (12). These findings emphasize that technology selection decisions have long-term economic implications for industrial organizations.

Technological readiness and infrastructure availability also play essential roles in determining the feasibility and effectiveness of production technology adoption. The successful implementation of new production technologies requires adequate infrastructure, skilled workforce capabilities, and organizational readiness. Strategic assessments of steel industry development have highlighted the importance of aligning technology selection with infrastructure capabilities, workforce readiness, and long-term industrial development strategies (2). Furthermore, the availability and reliability of raw materials and supply chain infrastructure significantly influence technology selection decisions, as production technologies must be compatible with available industrial resources and operational conditions.

Technological selection processes are inherently complex due to the interdependencies among technical, economic, environmental, and operational factors. These interdependencies require decision-makers to consider not only individual technology characteristics but also their interactions with organizational systems, production environments, and external regulatory frameworks. Research on optimal technology selection in industrial applications has demonstrated that selecting appropriate technologies requires systematic evaluation of technological alternatives, operational conditions, and performance criteria (13). Similarly, studies on clean hydrogen production technology selection have emphasized the importance of integrating technical feasibility, economic performance, and environmental sustainability into comprehensive technology evaluation frameworks (14). These findings highlight the need for integrated decision-making approaches capable of capturing the multidimensional nature of technology selection processes.

The steel industry faces unique challenges due to its capital-intensive nature, high energy consumption, and significant environmental impact. Steel production technologies must be evaluated not only based on technical and economic performance but also in terms of environmental sustainability, regulatory compliance, and long-term strategic alignment. The adoption of advanced production technologies has become essential for maintaining industrial competitiveness, achieving sustainability targets, and responding to evolving market demands. As global steel industries continue to transition toward low-carbon and digitally integrated production systems, the importance of structured and systematic technology selection processes has increased significantly.

Despite the growing importance of technology selection in the steel industry, there remains a need for comprehensive frameworks that identify, localize, and structurally analyze production technology selection indicators based on industry-specific conditions. Existing studies have primarily focused on technology performance evaluation, environmental assessment, or decision-making model applications, but limited attention has been given to systematically identifying and structuring technology selection indicators using integrated qualitative and structural modeling approaches. Furthermore, the localization of technology selection indicators within specific industrial contexts, such as Iran's steel industry, is essential for ensuring the relevance and applicability of technology selection frameworks. Industrial environments vary significantly in terms of infrastructure availability, resource accessibility, regulatory conditions, and technological readiness, necessitating context-specific technology selection models.

Given the strategic importance of technology selection in enhancing industrial competitiveness, improving environmental sustainability, and ensuring long-term operational efficiency, there is a critical need to systematically identify, analyze, and structurally level production technology selection indicators in steel manufacturing industries. Therefore, the aim of this study is to identify and level the production technology selection indicators in Iran's steel industry using qualitative content analysis, Delphi method, MICMAC analysis, and interpretive structural modeling.

Methods and Materials

This study, in terms of research philosophy, is grounded in a pragmatic paradigm and, from the perspective of purpose, is developmental. In terms of research approach, it follows an inductive approach, and in terms of nature, it is an exploratory–analytical study. From the perspective of data collection methodology, it is a mixed-methods study. Furthermore, in terms of data collection procedures, the research employs both library-based and field-based methods. Considering the four research steps, the statistical population and sample of the study are defined as follows.

The first step concerns the identification of production technology selection indicators in industries, and the statistical population includes articles related to the identification of production technology selection indicators in industries. The population size was 124 articles, and the sample size was determined to be 71 articles. The sampling method in this section was judgmental sampling. The second step focuses on the localization of production technology selection indicators in Iran's steel industry. The statistical population in this section includes academic faculty members and industry experts who possess knowledge of production technology selection indicators in Iran's steel industry. The sample size in this section was determined to be 12 experts, and the sampling method was purposive sampling. The third step addresses the analysis of influencing and influenced relationships among production technology selection indicators in Iran's steel industry. The statistical population includes academic faculty members and industry experts who are knowledgeable about the relationships among production technology selection indicators in Iran's steel industry, and 12 individuals were selected as the statistical sample using purposive sampling. The fourth step involves the leveling of production technology selection indicators in Iran's steel industry. The statistical population includes academic faculty members and industry experts who are knowledgeable about production technology selection in Iran's steel industry. The sample size in this section was determined to be 12 experts, and the sampling method was purposive sampling.

The data collection method and instrument in the first step consisted of a library-based study. The data collection instrument in this section involved extracting and recording information from various articles and books related to the research topic. The data collection method in the second, third, and fourth steps was field-based, and the data collection instrument in these steps was a questionnaire.

To assess the validity and quality of the instruments at each research step, validity and reliability were examined. In the first step, the research instrument was library-based. To ensure validity and reliability in this step, the Lincoln and Guba evaluation method, which is commonly applied to validate qualitative research, was employed. In this step, four criteria—credibility, dependability, transferability, and confirmability—were used to ensure validity and reliability. In this section, initially, 15 articles were subjected to content analysis and documented, and subsequently provided to the supervising and advisory professors. The validity and reliability of the examined items were confirmed. In the second step, although the study was quantitative, because it was expert-oriented, the same validation approach used in the first step was applied. In the third and fourth steps, the instrument used was a pairwise comparison questionnaire. The expert questionnaire was evaluated through the calculation of the consistency index. To assess the questionnaire, an index known as the inconsistency index was used. These indices indicate that if the inconsistency level of pairwise comparisons exceeds 0.10, it is preferable to revise the comparisons. Therefore, the maximum possible questions were presented to respondents in an optimal structure. Since all criteria were considered in this assessment and the designer could not introduce directional bias in the design of questions, reliability assessment was deemed unnecessary.

The data analysis method in the first step was the qualitative content analysis approach. Content analysis is a documentary method that examines communication messages in a systematic, objective, quantitative, and generalizable manner. In qualitative content analysis, efforts are made to identify and extract content categories present in communication messages through open coding, axial coding, and selective coding. Ultimately, by entering the codes into specialized NVivo software, the indicators were screened and finalized through an agreed-upon coding process. In the second step, the Delphi method was used to localize production technology selection indicators in Iran's steel industry. In the third step, to examine the influencing and influenced relationships among production technology selection indicators in Iran's steel industry, cross-impact analysis was conducted using MICMAC analysis to perform structural analysis in futures studies. To identify important and key components, both the Direct Method and the Indirect Method were applied. In the fourth step, Interpretive Structural Modeling (ISM) was used to level production technology selection indicators in Iran's steel industry.

Findings and Results

Initially, production technology selection indicators in industries were examined based on international and domestic articles, and qualitative analysis was conducted to establish an initial conceptual framework for the researcher. Table 1 presents the qualitative analysis of the reviewed articles.

Table 1. Production Technology Selection Indicators in Industries Extracted from International and Domestic Articles

No.	Indicator
1	Compatibility with the circular economy
2	Implementation speed
3	Capability to produce according to export standards
4	Equipment supply chain security
5	Energy efficiency
6	Digitalization capability and intelligentization using artificial intelligence
7	Product quality
8	Availability and sustainability of feedstock
9	Production flexibility
10	Return on investment and payback period
11	Technical and operational risk
12	Operating cost
13	Price acceptability and input volatility
14	Compliance with climate regulations and policies
15	Market and customer acceptance
16	Potential for reducing environmental pollutant emissions
17	Reliability of equipment supply
18	Long-term resilience and flexibility
19	Impact on employment and local communities
20	Legal and intellectual property considerations
21	Technology readiness for implementation
22	Capital investment cost
23	Energy infrastructure

Subsequently, Figures 1 and 2 present the output of frequently occurring words, diagrams, and graphical representations of production technology selection indicators in industries generated by NVivo 12 software.

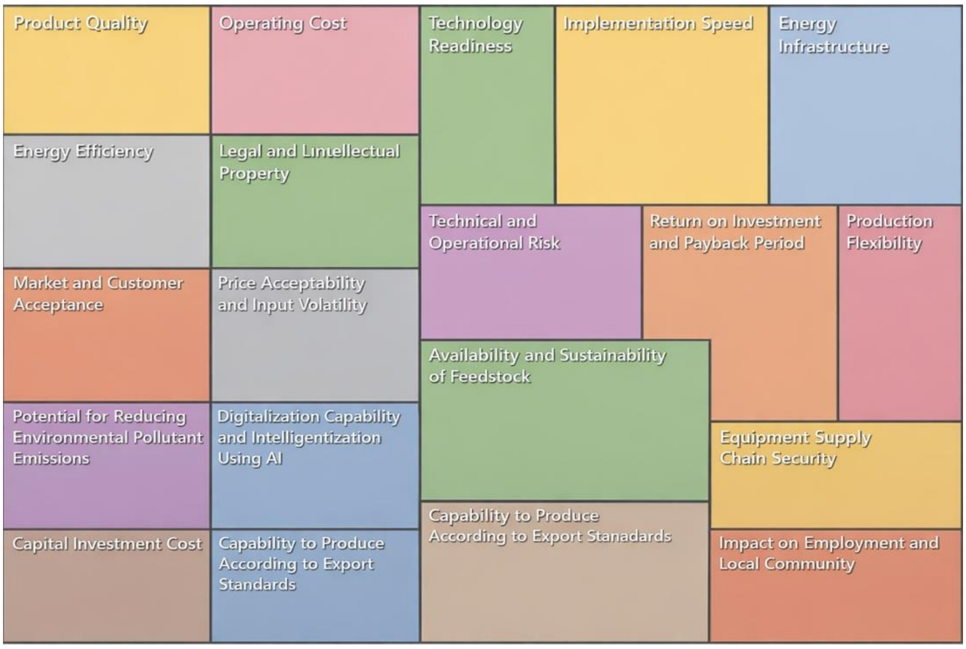

Figure 1. Category Diagram Output from NVivo 12 Software

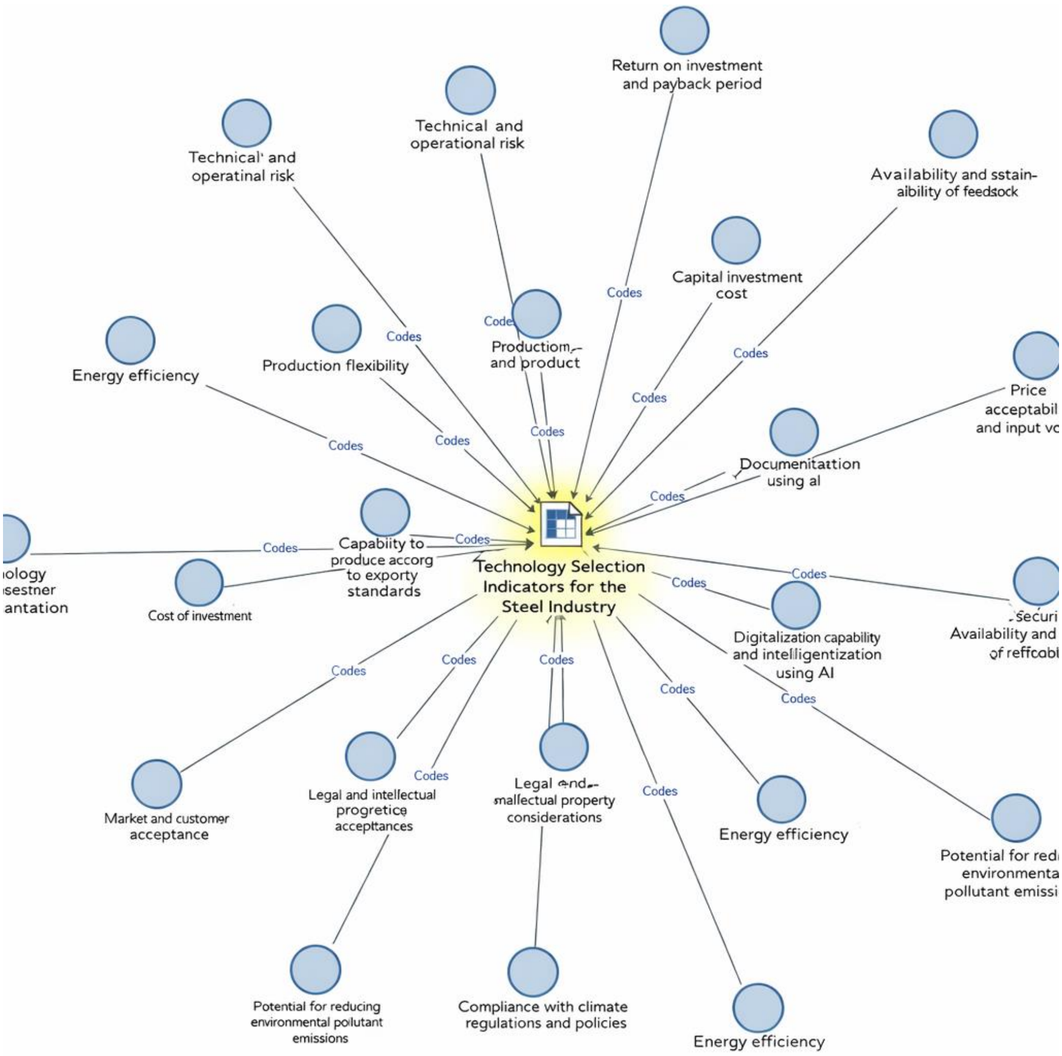

Figure 2. Code Diagram Output from NVivo 12 Software

Subsequently, in order to localize the production technology selection indicators in Iran's steel industry, the researcher consulted experts and, by providing explanations and applying the Delphi method, the indicators were localized according to the specific industry under investigation, namely the steel industry. In this section, the designed questionnaire was completed by the experts. The questionnaire included the question: "What are the production technology selection indicators in Iran's steel industry?" To answer this question, the 23 indicators extracted in the previous stage were presented to the experts in the form of a questionnaire. In this study, Kendall's coefficient of concordance was used to determine the degree of agreement among experts using the Delphi method. Kendall's coefficient of concordance is a measure used to determine the degree of coordination and agreement among multiple sets of rankings assigned by N individuals. This measure is particularly useful in studies related to inter-rater validity. To assess the overall agreement and consensus among participants, a Kendall's W coefficient greater than or equal to 0.50 was considered the criterion for agreement among participants' opinions.

The Kendall's W coefficient in the first round of the Delphi process was less than 0.50, indicating that the level of agreement among experts was not satisfactory. In the second round of the Delphi process, Kendall's W coefficient was greater than 0.50, indicating that the level of agreement among experts was satisfactory. Based on the difference in mean scores between the second and first rounds of expert opinions, six indicators reached consensus and were not re-evaluated in subsequent Delphi rounds. In the third round of the Delphi process, Kendall's W coefficient was greater than 0.50, indicating an acceptable level of agreement among experts. Based on the difference in mean scores between the third and second rounds, seven indicators reached consensus and were not re-evaluated in subsequent Delphi rounds. In the fourth round of the Delphi process, Kendall's W coefficient was greater than 0.50, indicating an acceptable level of agreement among experts. Based on the difference in mean scores between the fourth and third rounds, five indicators reached consensus and were not re-evaluated in subsequent Delphi rounds.

In the fifth round, the Delphi questionnaire containing five indicators was distributed among the experts, along with the mean score of each indicator from the fourth round and the score assigned by each expert in the previous round. After data collection in the fifth round, the mean score of each indicator was calculated, and the difference between the fifth and fourth rounds was determined. Indicators with a mean difference of less than 0.15 were considered to have reached consensus and were excluded from subsequent questionnaire distribution.

Table 2. Results of the Fifth Delphi Round and Calculation of Mean Differences Between the Fifth and Fourth Rounds

No.	Indicator	Mean Score (Fourth Round)	Mean Score (Fifth Round)	Mean Difference (Fifth–Fourth)
1	Compatibility with the circular economy	1.94	1.94	0.00
2	Availability and sustainability of feedstock	4.19	4.08	0.11
3	Production flexibility	3.52	3.66	0.14
4	Operating cost	3.52	3.66	0.14
5	Impact on employment and local community	2.66	2.56	0.10

As shown in Table 3, Kendall's W coefficient in the fifth round of the Delphi process was greater than 0.50, indicating an acceptable level of agreement among experts. Based on the difference in mean scores between the fifth and fourth rounds, five indicators reached consensus and were not re-evaluated in subsequent Delphi rounds.

Table 3. Results of Kendall's Coefficient of Concordance Test for the Fifth Delphi Round

Delphi Round	Number of Experts	Kendall's W	Chi-square Statistic	Degrees of Freedom	Significance Level (Sig.)
Fifth Round	12	0.577	523.31	4	0.000

Based on the results of the fifth Delphi round, experts reached consensus on all 23 indicators, and therefore, further questionnaire distribution was not required. Indicators with a mean score lower than 3 were eliminated at this stage. According to the results, out of the total 23 indicators, 8 indicators were eliminated, and 15 indicators were identified as the final production technology selection indicators in Iran's steel industry, as presented in Table 4.

Table 4. Production Technology Selection Indicators in Iran's Steel Industry

No.	Final Factors
1	Product quality
2	Production flexibility
3	Availability and sustainability of feedstock
4	Return on investment and payback period
5	Technical and operational risk
6	Technology readiness for implementation
7	Operating cost
8	Price acceptability and input volatility
9	Potential for reducing environmental pollutant emissions
10	Capital investment cost
11	Energy efficiency
12	Capability to produce according to export standards
13	Digitalization capability and intelligentization using artificial intelligence
14	Energy infrastructure
15	Equipment supply chain security

To achieve the research objective, this step examined the influencing and influenced relationships among production technology selection indicators in Iran's steel industry. A questionnaire consisting of the 15 identified indicators was used, structured in the form of pairwise comparisons. Respondents were asked to compare the indicators pairwise and determine the relationships between them. To perform cross-impact analysis of production technology selection indicators in Iran's steel industry, the MICMAC analysis method was applied.

Based on the aggregation of matrix evaluation values, the matrix fill rate was 82.66%, indicating a high and dispersed level of influence among indicators and reflecting the stability of the system. Out of a total of 186 evaluable relationships in the matrix, 39 relationships had a value of zero (no influence), 31 relationships had a value of one (weak influence), 75 relationships had a value of two (moderate influence), and 80 relationships had a value of three (strong influence). Furthermore, based on statistical indicators and after two data rotations, the matrix achieved 100% desirability and optimization, indicating the high validity of the questionnaire and its responses.

Table 5 presents the total number of rows and total number of columns separately for each indicator. The highest number of row totals corresponds to the indicator of technology readiness for implementation, while the lowest number of row totals corresponds to the product quality indicator. Furthermore, the highest number of column totals corresponds to the technical and operational risk indicator, and the lowest number of column totals corresponds to the technology readiness for implementation indicator. The total number of rows and columns is 421, which indicates the square structure (15 × 15) of the cross-impact matrix used in this study.

Table 5. Quantitative Size of Rows and Columns by Indicator

No.	Factor	Row Total (Influence)	Column Total (Dependence)
1	Technology readiness for implementation	41	8
2	Capital investment cost	35	17
3	Technical and operational risk	36	37
4	Production flexibility	32	34
5	Digitalization capability and intelligentization using artificial intelligence	28	36
6	Return on investment and payback period	22	25
7	Energy efficiency	31	32
8	Product quality	19	27
9	Operating cost	26	29
10	Capability to produce according to export standards	25	28
11	Energy infrastructure	22	25
12	Availability and sustainability of feedstock	29	28
13	Price acceptability and input volatility	27	28
14	Equipment supply chain security	21	36
15	Potential for reducing environmental pollutant emissions	27	31
Total	—	421	421

To examine the cross-impact effects among production technology selection indicators in Iran's steel industry, all analyses, including direct and indirect relationships among indicators, were conducted at three levels: 5%, 50%, and 100%. Relational diagrams were prepared for each of these three levels to ensure accurate judgment with a high level of confidence. It should be noted that calculating other levels is also possible; however, due to the absence of similar prior studies, other judgment levels were not considered. The rationale for selecting these three levels was to achieve the lowest possible level of relationships at the 5% level to identify the strongest indicators, to use the intermediate 50% level as a benchmark for identifying moderately to highly important indicators, and finally to use the 100% level to identify all indicators and their complete interrelationships.

The results of the direct and indirect influence analysis at the 5% level indicate that only the strongest evaluable relationships among the indicators were identified, and their influence intensity is numerically displayed above the relationships. The results of this analysis are presented in Figures 3 and 4.

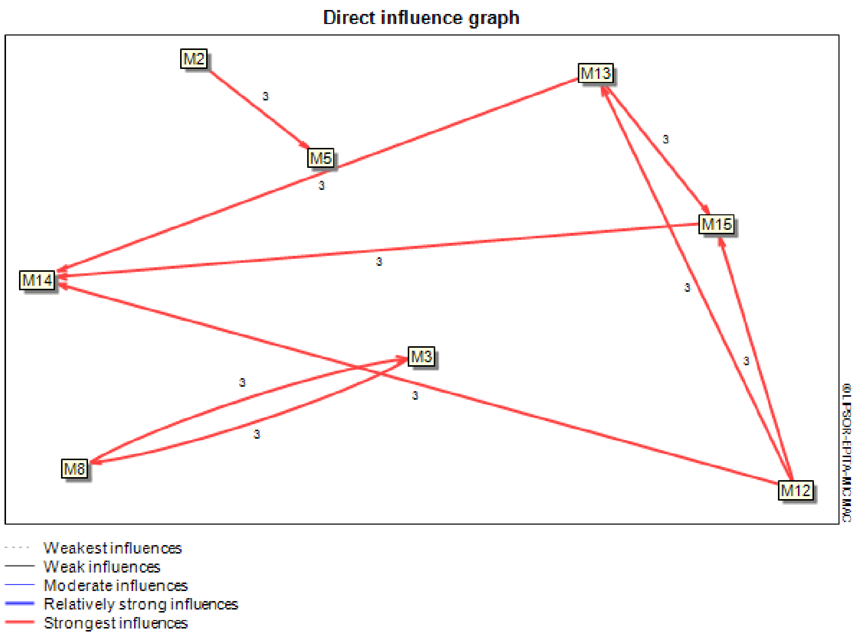

Figure 3. Direct Influence at the 5% Level

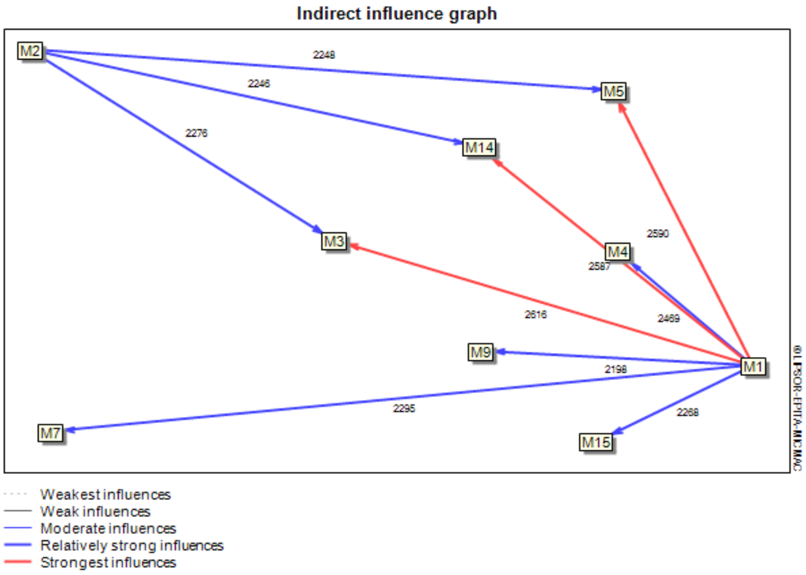

Figure 4. Direct and Indirect Influence at the 5% Level

The results of the direct and indirect influence analysis at the 50% level indicate that all evaluable relationships of moderate to high strength among the indicators were identified. All fifteen identified indicators demonstrated relationships characterized by moderate to high levels of direct and indirect influence. The analysis results confirm that all fifteen indicators exhibit at least moderate intensity relationships. The results of this analysis are presented in Figures 5 and 6.

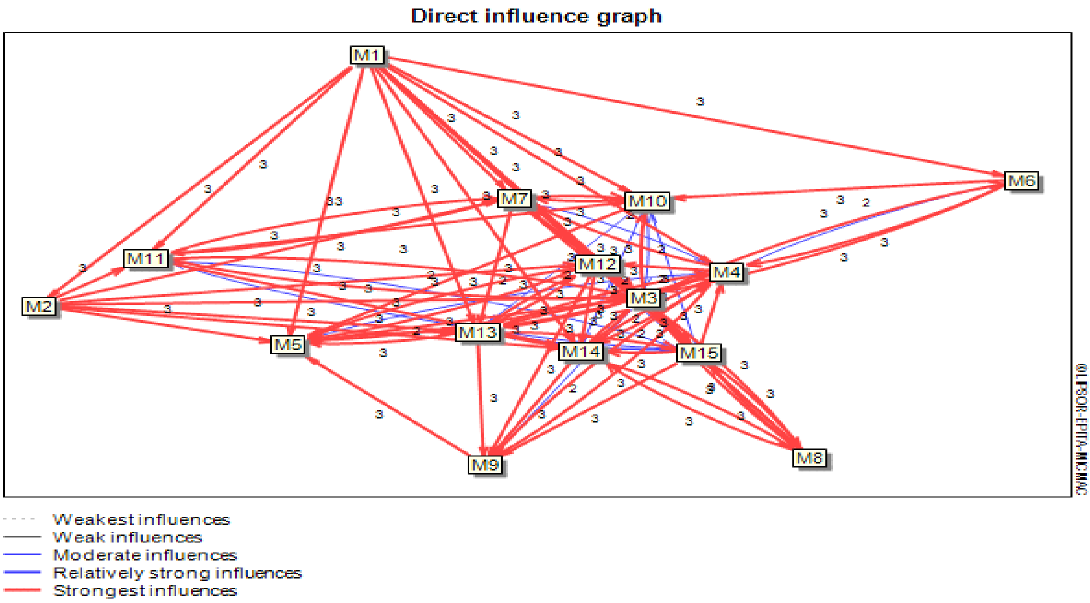

Figure 5. Direct Influence at the 50% Level

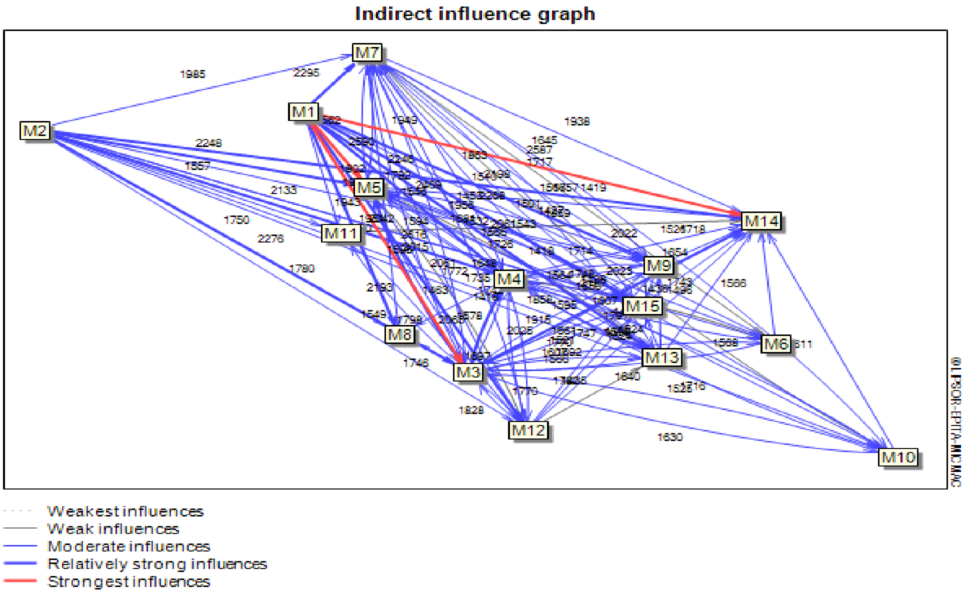

Figure 6. Direct and Indirect Influence at the 50% Level

The results of the direct and indirect influence analysis at the 100% level indicate that all evaluable relationships among the indicators were identified, and all fifteen indicators recognized by the expert panel exhibited both direct and indirect influence relationships. This finding demonstrates that all identified indicators were agreed upon by the expert panel and were confirmed as production technology selection indicators in Iran’s steel industry. The results of this analysis are presented in Figures 7 and 8.

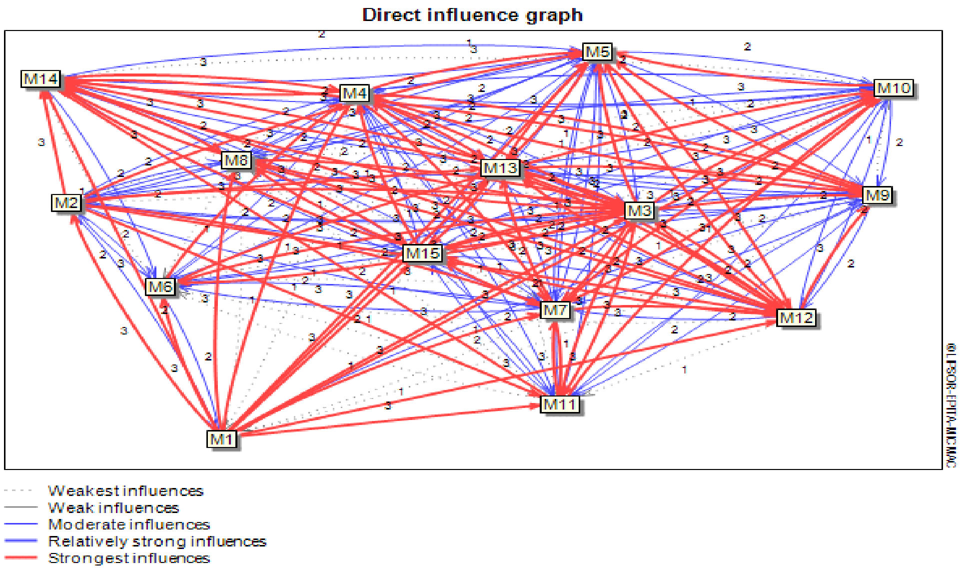

Figure 7. Direct Influence at the 100% Level

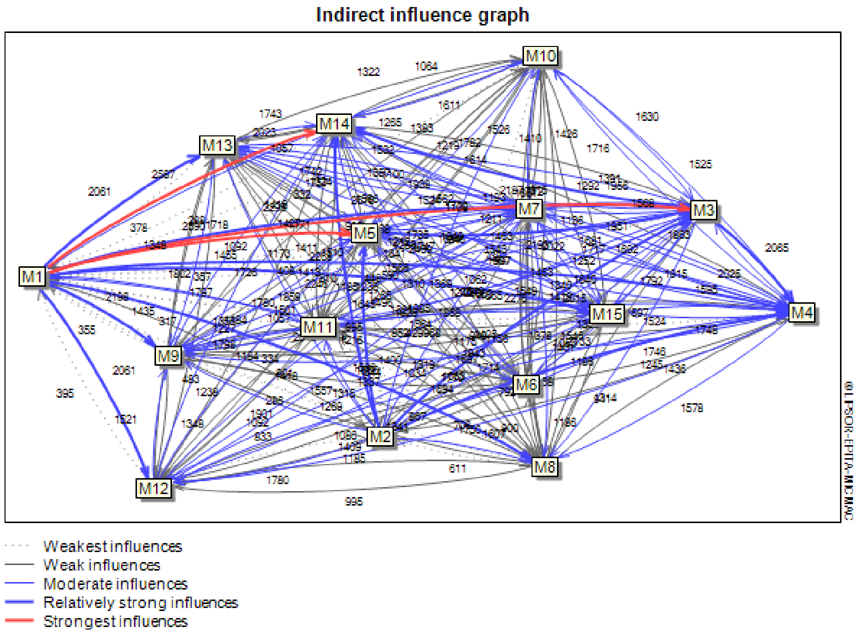

Figure 8. Direct and Indirect Influence at the 100% Level

In this step, the researcher consulted experts in order to level the production technology selection indicators in Iran's steel industry and, by distributing a questionnaire, sought to level the 15 indicators identified in the previous stages. To achieve the objective of this step, a questionnaire consisting of the 15 identified indicators, as presented in Table 6, was used. The questionnaire was structured in the form of pairwise comparisons, and respondents were asked to determine the relationships between the factors by comparing them pairwise, specifying whether there was no relationship, a unidirectional relationship, or a bidirectional relationship.

Table 6. Symbols of Production Technology Selection Indicators in Iran's Steel Industry in ISM

No.	Production Technology Selection Indicator in Iran's Steel Industry	Symbol
1	Technology readiness for implementation	C1
2	Capital investment cost	C2
3	Technical and operational risk	C3
4	Production flexibility	C4
5	Digitalization capability and intelligentization using artificial intelligence	C5
6	Return on investment and payback period	C6
7	Energy efficiency	C7
8	Product quality	C8
9	Operating cost	C9
10	Capability to produce according to export standards	C10
11	Energy infrastructure	C11
12	Availability and sustainability of feedstock	C12
13	Price acceptability and input volatility	C13
14	Equipment supply chain security	C14
15	Potential for reducing environmental pollutant emissions	C15

Subsequently, using the ISM structural self-interaction questionnaire and constructing the self-interaction matrix based on the highest frequency of responses, the initial reachability matrix was developed, and the corresponding information is presented in Table 7.

Table 7. Initial Reachability Matrix

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15
C1		V	V	V	V	V	V	V	V	V	V	V	V	V	V
C2			V	V	V	V	V	V	V	V	V	V	V	V	V
C3				V	V	V	X	X	X	X	X	X	X	V	V
C4					V	A	A	V	X	A	A	X	X	A	A
C5						V	V	V	A	V	V	V	V	V	V
C6							X	O	O	A	O	O	O	V	V
C7								X	V	V	V	V	V	V	V
C8									X	O	O	O	O	V	V
C9										A	A	A	A	A	A
C10											V	V	V	V	V
C11												O	O	V	V
C12													X	V	V
C13														V	V
C14															A
C15															

Based on the information obtained from Table 7 and following the ISM procedure, the final reachability matrix of the study was developed, and its complete details are presented in Table 8.

Table 8. Final Reachability Matrix

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15
C1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
C2	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1
C3	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1
C4	0	0	1*	1	1	1*	1*	1	1	1*	1*	1	1	1*	1*
C5	0	0	1*	1*	1	1	1	1	1*	1	1	1	1	1	1
C6	0	0	1*	1	1*	1	1	1*	1*	1*	1*	1*	1*	1	1
C7	0	0	1	1	1*	1	1	1	1	1	1	1	1	1	1
C8	0	0	1	1*	1*	1*	1	1	1	1*	1*	1*	1*	1	1
C9	0	0	1	1*	1	1*	1*	1	1	1*	1*	1*	1*	1*	1*
C10	0	0	1	1	1*	1	1*	1*	1	1	1	1	1	1	1
C11	0	0	1	1*	1*	1*	1*	1*	1	1*	1	1*	1*	1	1
C12	0	0	1	1	1*	1*	1*	1*	1	1*	1*	1	1	1	1
C13	0	0	1	1	1*	1*	1*	1*	1	1*	1*	1	1	1	1
C14	0	0	1*	1	1*	0	0	1*	1	0	0	1*	1*	1	0
C15	0	0	1*	1	1*	0	0	1*	1	0	0	1*	1*	1	1

To determine the levels of dimensions, as described in the previous stage, it is necessary to identify the reachability set, antecedent set, and intersection set, which are presented in Table 9.

Table 9. Determination of Model Levels

Symbol	Factors	Reachability Set	Antecedent Set	Intersection Set	Level
C1	Technology readiness for implementation	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15	1	1	Fifth
C2	Capital investment cost	2,3,4,5,6,7,8,9,10,11,12,13,14,15	1,2	2	Fourth
C3	Technical and operational risk	3,4,5,6,7,8,9,10,11,12,13,14,15	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15	3,4,5,6,7,8,9,10,11,12,13,14,15	First
C4	Production flexibility	3,4,5,6,7,8,9,10,11,12,13,14,15	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15	3,4,5,6,7,8,9,10,11,12,13,14,15	First
C5	Digitalization capability and intelligentization using artificial intelligence	3,4,5,6,7,8,9,10,11,12,13,14,15	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15	3,4,5,6,7,8,9,10,11,12,13,14,15	First

C6	Return on investment and payback period	3,4,5,6,7,8,9,10,11,12,13,14,15	1,2,3,4,5,6,7,8,9,10,11,12,13	3,4,5,6,7,8,9,10,11,12,13	Third
C7	Energy efficiency	3,4,5,6,7,8,9,10,11,12,13,14,15	1,2,3,4,5,6,7,8,9,10,11,12,13	3,4,5,6,7,8,9,10,11,12,13	Third
C8	Product quality	3,4,5,6,7,8,9,10,11,12,13,14,15	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15	3,4,5,6,7,8,9,10,11,12,13,14,15	First
C9	Operating cost	3,4,5,6,7,8,9,10,11,12,13,14,15	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15	3,4,5,6,7,8,9,10,11,12,13,14,15	First
C10	Capability to produce according to export standards	3,4,5,6,7,8,9,10,11,12,13,14,15	1,2,3,4,5,6,7,8,9,10,11,12,13	3,4,5,6,7,8,9,10,11,12,13	Third
C11	Energy infrastructure	3,4,5,6,7,8,9,10,11,12,13,14,15	1,2,3,4,5,6,7,8,9,10,11,12,13	3,4,5,6,7,8,9,10,11,12,13	Third
C12	Availability and sustainability of feedstock	3,4,5,6,7,8,9,10,11,12,13,14,15	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15	3,4,5,6,7,8,9,10,11,12,13,14,15	First
C13	Price acceptability and input volatility	3,4,5,6,7,8,9,10,11,12,13,14,15	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15	3,4,5,6,7,8,9,10,11,12,13,14,15	First
C14	Equipment supply chain security	3,4,5,8,9,12,13,14	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15	3,4,5,8,9,12,13,14	First
C15	Potential for reducing environmental pollutant emissions	3,4,5,8,9,12,13,14,15	1,2,3,4,5,6,7,8,9,10,11,12,13,15	3,4,5,8,9,12,13,15	Second

Based on Table 9 and the identified levels, the interpretive structural model was developed and graphically represented as shown in Figure 9.

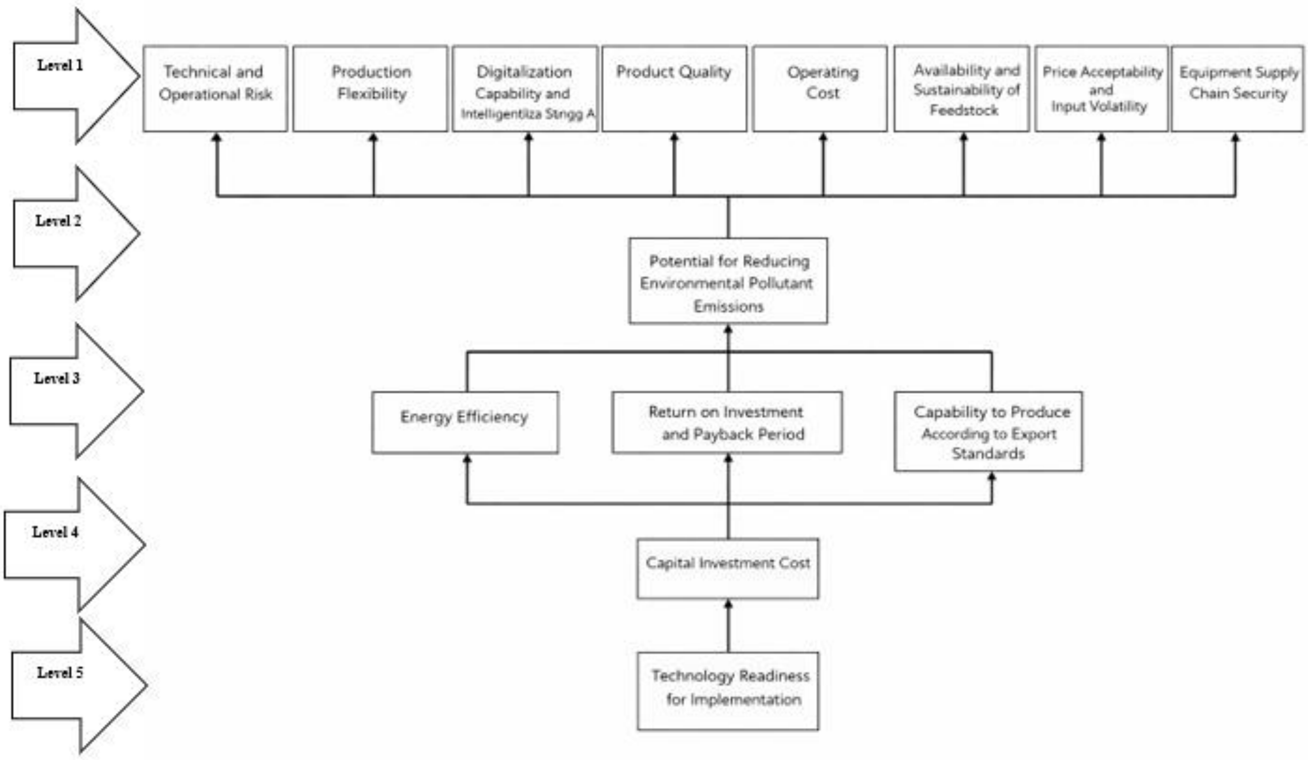

Figure 9. Final Leveling of Production Technology Selection Indicators

Discussion and Conclusion

The findings of this study provide a comprehensive and structured framework for understanding the production technology selection indicators in Iran's steel industry and their hierarchical relationships. Based on qualitative content analysis, Delphi consensus, MICMAC cross-impact analysis, and interpretive structural modeling (ISM), fifteen key indicators were identified and structurally classified according to their levels of influence and dependence. The results revealed that indicators such as technical and operational risk, production flexibility, digitalization capability and intelligentization using artificial intelligence, product quality, operating cost, availability and sustainability of feedstock, price acceptability and input volatility, and equipment supply chain security were among the most dependent indicators. This implies that these factors are significantly influenced by foundational structural and strategic elements such as technology readiness, capital investment cost, energy infrastructure, and return on investment. These findings emphasize that production technology selection is not determined by isolated performance variables but rather emerges from a systemic interaction of technological, economic, environmental, and operational dimensions. This systemic perspective aligns with previous research emphasizing that steel production technology selection involves complex interdependencies among technical feasibility, infrastructure readiness, and long-term operational sustainability (6, 7).

One of the most significant findings of this study is the critical role of technology readiness for implementation and capital investment cost as foundational driving indicators influencing multiple downstream technology selection criteria. Technology readiness serves as a prerequisite for the adoption and operationalization of advanced production technologies. This finding is consistent with prior research indicating that technological maturity and readiness directly determine the feasibility and effectiveness of production technology implementation in industrial environments (9). Furthermore, capital investment cost was identified as a key structural factor influencing return on investment, energy efficiency, and export capability. Steel production technologies require substantial capital investment, and financial feasibility plays a decisive role in determining technology adoption decisions. Previous studies have similarly emphasized that financial performance indicators such as investment cost and payback period significantly influence industrial technology selection and competitiveness in steel manufacturing (11, 12). This confirms that financial readiness and economic feasibility remain central to strategic technology adoption decisions in capital-intensive industries such as steel manufacturing.

The findings also demonstrated that environmental performance indicators, particularly the potential for reducing environmental pollutant emissions, occupy an intermediate structural level, connecting foundational technological and financial indicators with operational performance outcomes. This highlights the growing importance of environmental sustainability in production technology selection. Steel production is one of the largest contributors to industrial carbon emissions globally, and environmental performance has become a critical criterion in evaluating production technologies. Previous studies have demonstrated that environmentally sustainable technologies such as carbon capture systems and clean short-process production methods significantly improve environmental performance while maintaining production efficiency (3, 4). Furthermore, policy-driven technology selection pathways aimed at achieving carbon neutrality have emphasized the importance of selecting environmentally sustainable technologies to ensure regulatory compliance and long-term industrial sustainability (10). The positioning of environmental indicators as structurally influential but dependent factors reflects the reality that environmental performance outcomes are largely determined by upstream technological and financial decisions.

Another key finding of this study is the central role of energy efficiency, return on investment, and export capability as intermediate structural indicators linking foundational drivers to operational performance outcomes. Energy efficiency is particularly critical in steel production due to the energy-intensive nature of steel manufacturing processes. Improvements in energy efficiency directly affect production costs, environmental performance, and operational sustainability. This finding is consistent with prior research demonstrating that energy-efficient steel production technologies significantly enhance operational efficiency while reducing environmental impact and production costs (3). Similarly, return on investment and payback period serve as key financial performance indicators influencing technology adoption decisions. Technologies that offer faster payback periods and higher financial returns are more likely to be adopted by industrial organizations. This finding aligns with previous research emphasizing the importance of economic performance indicators in production technology selection frameworks (6). Additionally, the capability to produce according to export standards was identified as a structurally important factor, highlighting the importance of technology selection in enhancing global competitiveness. Steel production technologies must meet international quality and regulatory standards to enable export competitiveness, which is consistent with prior research highlighting the strategic importance of technological capability in improving industrial competitiveness and global market access (2).

The results further revealed that operational performance indicators such as product quality, production flexibility, operating cost, and supply chain security are among the most dependent indicators in the structural model. This suggests that operational performance outcomes are largely influenced by upstream strategic and technological factors rather than serving as independent drivers of technology selection. Product quality is a critical performance indicator in steel manufacturing, as it directly affects customer satisfaction, market competitiveness, and regulatory compliance. Previous studies have shown that advanced production technologies significantly improve product quality by enhancing process precision, consistency, and technological control (12). Similarly, production flexibility enables steel manufacturers to respond to changing market demands and production requirements. Flexible production technologies allow manufacturers to produce a wider range of steel products efficiently, improving operational adaptability and competitiveness. This finding is consistent with prior research demonstrating that flexible production technologies enhance industrial responsiveness and operational efficiency (8).

Digitalization capability and intelligentization using artificial intelligence were also identified as highly dependent indicators, reflecting their reliance on foundational technological and infrastructural readiness. Digital technologies enhance production monitoring, predictive maintenance, process optimization, and decision-making efficiency. Previous studies have demonstrated that digital information selection and digital technology adoption significantly improve technological efficiency, operational performance, and environmental sustainability (5). Additionally, digital transformation enables steel manufacturers to integrate advanced technologies such as automation, artificial intelligence, and data analytics, improving production efficiency and reducing operational risks. Research on green innovation systems has similarly emphasized the importance of technological innovation and digital transformation in enabling sustainable steel production and enhancing technological competitiveness (1). These findings confirm that digitalization is not an isolated technological feature but rather an outcome enabled by upstream investments in technological infrastructure and organizational readiness.

The importance of feedstock availability and supply chain security as dependent indicators highlights the critical role of resource availability and logistical infrastructure in production technology selection. Steel production technologies must be compatible with available raw materials and supply chain conditions to ensure operational continuity and efficiency. Supply chain disruptions can significantly affect production stability, operational efficiency, and financial performance. Previous studies have emphasized that technological compatibility with supply chain infrastructure and raw material availability is essential for ensuring sustainable and efficient production operations (13). Furthermore, strategic infrastructure readiness and industrial ecosystem development have been identified as critical enablers of sustainable steel production and technological competitiveness (2).

Overall, the findings of this study confirm that production technology selection in the steel industry is a complex, multidimensional, and hierarchical decision-making process influenced by interrelated technological, economic, environmental, and operational factors. Foundational factors such as technology readiness and capital investment cost serve as primary drivers that shape environmental performance, financial feasibility, and operational outcomes. These findings align with previous research demonstrating that optimal technology selection requires integrated evaluation frameworks capable of capturing the multidimensional and systemic nature of industrial technology adoption decisions (14, 15). Furthermore, the structural relationships identified in this study provide valuable insights into the causal pathways through which technological, financial, and environmental factors influence operational performance outcomes in steel production systems.

One of the primary limitations of this study is the reliance on expert judgment in the Delphi and structural modeling phases, which may introduce subjective bias despite efforts to achieve consensus and consistency. Although the experts selected possessed substantial academic and industrial experience, their perspectives may not fully represent all stakeholders within the steel industry. Additionally, the study was conducted within the specific context of Iran's steel industry, and the findings may be influenced by local industrial infrastructure, regulatory conditions, and technological readiness. As a result, the generalizability of the findings to other countries or industrial contexts may be limited. Another limitation is the static nature of the structural model, which does not account for dynamic technological evolution and changing industrial conditions over time. Technological innovation, regulatory changes, and market dynamics can alter the relative importance and structural relationships of technology selection indicators. Finally, the study focused primarily on qualitative and structural analysis and did not incorporate quantitative performance data or simulation-based validation of the identified relationships.

Future research should aim to validate and extend the structural model identified in this study by incorporating quantitative performance data and empirical testing. Researchers can apply advanced statistical modeling techniques such as structural equation modeling or system dynamics modeling to examine causal relationships among technology selection indicators more rigorously. Comparative studies across different countries and industrial contexts would also be valuable in assessing the generalizability of the findings and identifying context-specific differences in technology selection criteria. Longitudinal studies could examine how technology selection indicators evolve over time in response to technological innovation, policy changes, and market dynamics. Additionally, future research could explore the integration of artificial intelligence and machine learning techniques into technology selection frameworks to enhance decision-making accuracy and predictive capability.

Industrial decision-makers should prioritize foundational technological readiness and financial feasibility when selecting production technologies, as these factors significantly influence downstream operational and environmental performance outcomes. Investment strategies should focus on building technological infrastructure and ensuring organizational readiness to support advanced production technologies. Policymakers should develop supportive regulatory frameworks and financial incentives to facilitate the adoption of environmentally sustainable steel production technologies. Steel manufacturing firms should also invest in digital transformation initiatives to enhance production efficiency, improve operational flexibility, and strengthen supply chain resilience. Finally, technology selection decisions should be approached as strategic, system-level decisions that consider long-term sustainability, economic performance, and technological compatibility rather than focusing solely on short-term operational performance.

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Authors' Contributions

All authors equally contributed to this study.

Declaration of Interest

The authors of this article declared no conflict of interest.

Ethical Considerations

All ethical principles were adheried in conducting and writing this article.

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.

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