Ferdowsi University of Mashhad

JOURNAL OF SYSTEMS THINKING IN PRACTICE

Print ISSN: 2980-9460
Online ISSN: 2821-1669
Volume 3, Issue 4, fall, 2024

JOURNAL OF SYSTEMS THINKING IN PRACTICE (JSTINP), Quarterly

Web: jstinp.um.ac.ir

In the Name of God, the Compassionate, the Merciful

Journal of Systems Thinking in Practice (STINP)

FERDOWSI UNIVERSITY OF MASHHAD
Editorial Office:Systems Thinking In Practice Group, Faculty of Economics and Administrative sciences, Ferdowsi University of Mashhad, Mashhad, Iran. Phone: +98(51)3880-6356

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About the journal

- **Publisher:** Ferdowsi University of Mashhad, Iran
- **Adheres to:** the guidelines of the Committee on Publication Ethics (COPE)
- **Review time:** 65 days
- **Frequency:** Quarterly
- **Open access:** Yes
- **Licensed by:** CC BY 4.0
- **Policy:** Duble blind peer-reviewed
- **Indexed and Abstracted:** Yes
- **Language:** English
- **Article Processing Charges:** No
- **Contact email:** jstinp@um.ac.ir

Publication Date:

Journal of Systems Thinking in Practice (JSTINP) is published 4 times a year. Volume 3, Issue 4, December 2024.

JOURNAL OF SYSTEMS THINKING IN PRACTICE (JSTINP), Quarterly

Web: jstinp.um.ac.ir

Volume 3, Issue 4, 2024

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Journal of Systems Thinking in Practice
JSTINP, *QUARTERLY*
Homepage: jstinp.um.ac.ir
Online ISSN: 2821-1669, Print ISSN: 2980-9460
Research Article
DOI: 10.22067/JSTINP.2024.89351.1115
JSTINP 2024; Vol. 3, No. 4

An Analysis of Supply Chain Macro-Strategies in the Context of Industry 4.0 with a System Dynamics Approach (The Case of: Iran's Steel Supply Chain)

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How to cite this article

Motallebi, S., Zandieh, M., Alem Tabriz, A., 2024. An Analysis of Supply Chain Macro-Strategies in the Context of Industry 4.0 with a System Dynamics Approach (The Case of: Iran's Steel Supply Chain). *Journal of Systems Thinking in Practice*, 3(4), pp.1 -35. doi: 10.22067/jstinp.2024.89351.1115

URL: https://jstinp.um.ac.ir/article_46058.html.

ABSTRACT

Forward-thinking decisions and adopting cutting-edge technologies typically influence the management of large, multi-level supply chains. Given the various raw materials, semi-finished products, and final goods in these multi-level supply chains, balancing imports and exports is one of the most significant challenges and macro-level issues facing countries. System dynamics simulation is a powerful tool for analyzing macro-level issues, as it can predict future system behavior based on current conditions. In this research, Iran's steel supply chain was selected as a case study to assess future trends at the macro level under the influence of Industry 4.0. Industry 4.0 encompasses a range of innovative technologies that can improve supply chain efficiency. For this purpose, AnyLogic software was used to simulate the model. According to the system dynamics simulation results, keeping a balance between supply and demand at each stage of the supply chain plays a crucial role in increasing efficiency and profitability. Additionally, macro-level policies such as budget allocation, export rate, and support for investments in various parts of the supply chain directly impact this chain's performance. Sensitivity analysis revealed that increasing the budget and production capacity in the direct reduced iron (DRI) and crude steel sectors has a greater impact on the overall profitability of the chain, and exporting crude steel can be a significant way to increase revenue and foreign exchange earnings for the country.

Keywords

System dynamics simulation, Multi-level supply chain, Supply chain macro-level, Industry 4.0, Iran's steel supply chain.

Article history

Received: 2024-08-12
Revised: 2024-11-08
Accepted: 2024-12-05
Published (Online): 2024-12-20

Number of Figures: 26 **Number of Tables: 11** **Number of Pages: 35** **Number of References:20**

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1. Introduction

Industry 4.0 has transformed manufacturing by introducing digital technologies to create smart, interconnected factories. This connectivity enables real-time data collection and analysis, enhancing efficiency, productivity, and flexibility.

This concept can also be manifested in large supply chains by integrating the capabilities of manufacturing units into cloud platforms (Zhu et al., 2022).

Large supply chains, with their multiple levels of producers and consumers and diverse interconnections, present significant complexities in management and control. Global competition in recent years has compelled organizations to produce products with lower costs, higher quality, and greater reliability and flexibility. In this regard, supply chains have significantly improved production efficiency (Luthra and Mangla, 2018). Large supply chains are important for gaining a competitive advantage in the global market. Since researchers have placed greater emphasis on supply chain research, a broad literature has been established in this field (Kache and Seuring, 2017).

Multi-level supply chains, which cover raw materials, semi-finished products, and finished products from production stages to end consumption, can extend from the local or national level to the global level. Imports and exports are among the most important factors influencing large, multi-level supply chains, and various factors can contribute to improving efficiency and increasing the value of the supply chain (Tahami and Fakhravar, 2020; Golgeci et al., 2020). These include:

- **Using domestic resources or imports:** If the raw materials for each level of the supply chain are produced domestically, choosing between using these raw materials or importing raw materials from abroad can be a significant challenge.
- **Meeting domestic needs or exports:** Exporting products to other countries can contribute to trade diversification and provide greater resilience in the face of various regional risks (such as economic or natural crises). If products are produced in sufficient quantities domestically and there is no need to export, it can help meet domestic needs and strengthen the domestic economy.

Overall, macro-level supply chain strategies and the balance between exports and imports in multi-level supply chains contribute to improved performance and increased added value, leading to better efficiency. Macro-level supply chain strategies are pivotal in shaping a country's economy. These strategies encompass a wide range of coordinated and integrated approaches to manage the entire supply chain, from procuring raw materials to delivering finished goods to consumers and determining the level of imports and exports. By improving the flow of goods and services, countries can gain a competitive advantage in the global market (Gereffi et al., 2021).

The steel supply chain is a complex multi-level supply chain that begins with iron ore extraction and ends with producing steel products. Each stage depends on the next in this chain, and any disruption in one stage can affect the entire chain (Figure 1). In this context, presenting a model that considers the macro-level supply and demand variables of products throughout the steel supply chain (from iron ore, concentrate, pellet, direct reduced iron, crude steel, and steel consumption and recycling) and using simulation techniques, models the future changes of this industry, can play a significant role in decision-making in the steel supply chain to improve specific production methods.

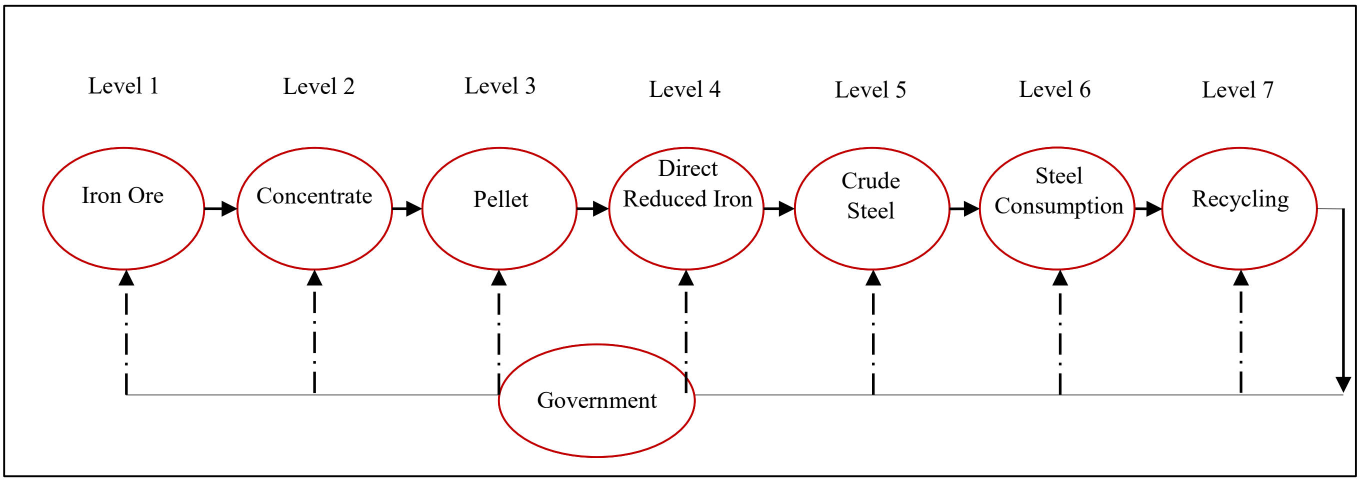

Figure 1. Steel supply chain

Iran's steel supply chain has numerous comparative advantages in terms of energy availability, energy costs, raw material and iron ore mines, and a skilled workforce at a low cost. These advantages, coupled with adopting advanced production technologies and the right strategies, can play a significant role in competing in the global steel market. Table 1 shows the crude steel production of the world's top 20 producers over the decade ending in 2022. Iran currently ranks 10th (Steel Statistical Yearbook, 2022).

Table 1. The world's top 20 producers over the decade ending in 2022

Rank (2022)	Year / Country	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
—	World	1649	1670	1620	1606	1675	1808	1874	1878	1952	1885
1	China	779	823	804	787	832	920	995	1065	1033	1018
2	India	81	87	90	96	102	109	111	100	144	154
3	Japan	111	111	105	105	105	104	99	83	96	89
4	United States	87	88	79	79	82	87	88	73	86	81
5	Russia	69	72	71	71	71	72	72	72	76	72
6	South Korea	66	72	70	69	71	73	71	67	70	66
7	Turkey	35	34	32	33	38	37	34	36	40	35
8	Germany	43	43	43	42	44	42	40	36	40	37
9	Brazil	34	34	33	30	34	35	33	31	36	34
10	Iran	15	16	16	18	22	25	26	29	29	31
11	Italy	24	24	22	23	24	25	23	20	24	22
12	Taiwan	22	23	21	22	23	23	22	21	23	21
13	Vietnam	6	6	6	8	10	16	18	20	23	20
14	Ukraine	33	27	23	24	23	21	21	21	21	6
15	Mexico	18	19	18	19	20	20	18	17	19	18
16	Indonesia	3	4	5	5	5	6	8	9	14	16
17	Spain	14	14	15	14	15	14	14	11	14	12
18	France	16	16	15	15	16	15	14	12	14	12
19	Canada	12	13	13	13	14	13	13	11	13	12
20	Egypt	7	7	6	5	7	8	7	8	10	10

Figure 2 depicts the trend in crude steel production for the top ten crude steel-producing countries from 2013 to 2022. Given that China accounts for 54% of the world's crude steel production, it has been excluded from the chart to better visualize other countries' production trends. As observed, Iran's crude steel production has shown an upward trend over the past decade.

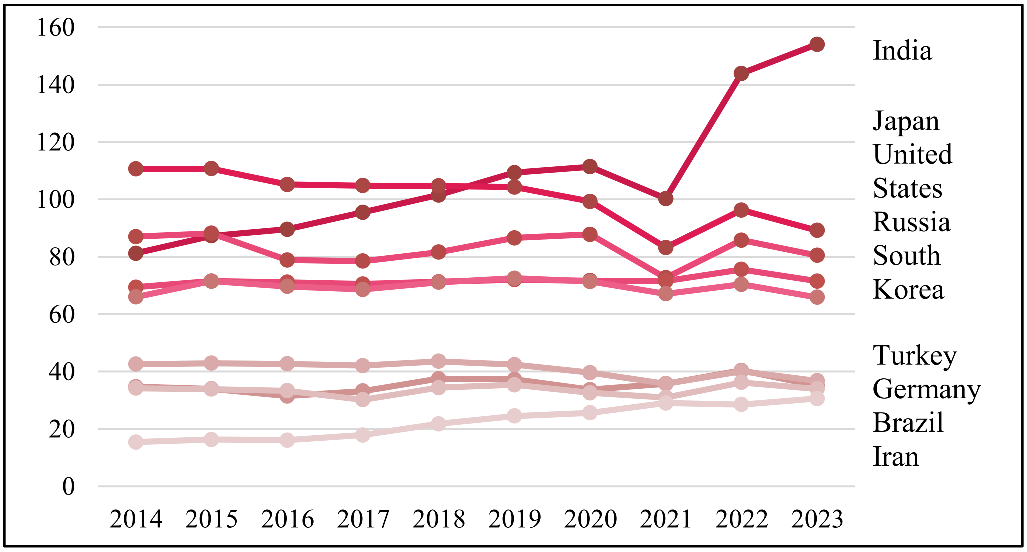

Figure 2. The trend in crude steel production for the top ten countries from 2013 to 2022 (Except China)

Figure 3 illustrates the top ten crude steel producers in 2022. China ranks first with a 54% share of the world's crude steel production, while Iran is the tenth largest producer with a 0.16% share.

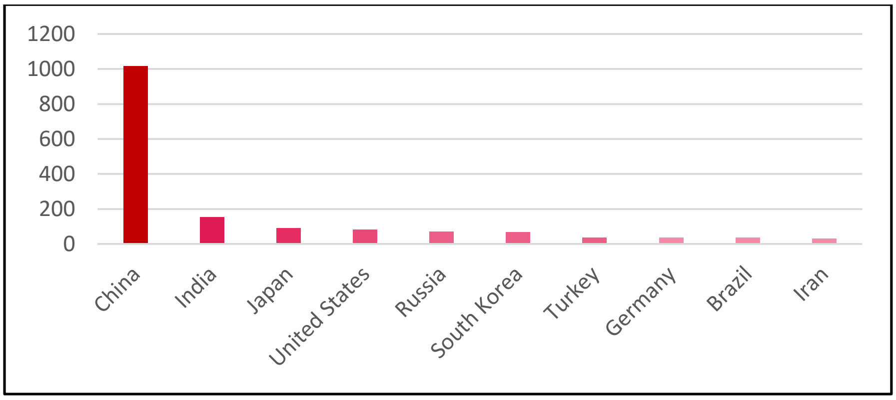

Figure 3. The top ten crude steel producers in 2022

Therefore, based on these statistics, Iran's steel supply chain can be a suitable case study for validating our model. This research uses system dynamics simulation to model the multi-level supply chain. Forrester first developed system dynamics to understand the structure and dynamics of a system. It is a method for studying, analyzing, and simulating dynamic social, economic, and managerial systems, ultimately leading to recommendations for improving them.

This research aims is to develop a comprehensive strategy for macro-level policies in a multi-level supply chain. The main variables include export rates, import rates, production rates, capacity development costs, capacity creation rates, capacity depreciation rates, product inventory, excess demand, demand for products at each level, demand growth rate, product sales rate, and total profit for each level of the multi-level supply chain This research will be conducted over a ten years.

The research question is: How can system dynamics modeling be used to develop a comprehensive strategy for macro-level policies in Iran's steel supply chain? And will these policies be affected by Industry 4.0?

In the following sections of this research, the literature review is presented in Section 2. The research methodology is discussed in Section 3, and the modeling results are presented in Section 4. Finally, the results are summarized in Section 5.

2. literature review

In order to conduct this research and identify the key variables and parameters of the problem, this study first reviewed the previous literature in this field. Generally, these research works can be categorized into three main groups (Figure 4).

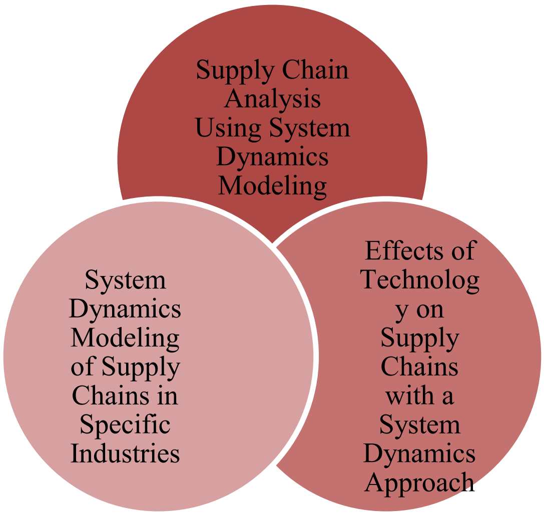

Figure 4. General classification of previous studies

2.1. Supply chain analysis using system dynamics modeling

This group of articles uses system dynamics to analyze and model supply chains. These articles delve into the concept of supply chain, production rate, inventory level, and other influencing factors. Özbayrak et al. (2007) modeled a supply chain system using system dynamics to analyze and understand the dynamic behavior of supply chains. The authors limited the system dynamics chain to a factory and production system, considering variables such as production rate, inventory level, order rate, lead time for raw materials, and production time in this model.

Ghadge et al. (2020) developed a model using system dynamics in a study aimed at analyzing the impact of implementing Industry 4.0 on supply chains and creating an implementation framework considering potential drivers and barriers. Four sets of variables influencing Industry 4.0 were used in this dynamic model. These four sets included strategic, technological, legal, ethical, and organizational factors. This study discussed several implementation challenges and proposed a framework for effectively adapting and transferring the Industry 4.0 concept to the supply chain. Rebs et al. (2019) also studied system dynamics modeling for sustainable supply chain management by reviewing the literature and a system thinking approach. They tracked global economic systems and environmental and social impacts in previous studies. Although system dynamics modeling is suitable for simulating and analyzing complex and dynamic systems and supporting long-term and strategic decision-making, this article presents economic, environmental, and social criteria related to macro and micro levels of supply chain dynamics analysis.

2.2. Effects of technology on supply chains with a system dynamics approach

In this group, system dynamics is used to investigate the impacts of technologies such as

Industry 4.0 and blockchain on supply chains and to propose implementation frameworks. For instance, Nuñez Rodriguez et al. (2021) developed a system dynamics model for additive manufacturing supply chain management, aiming to visualize supply chain behavior when adopting a disruptive technology like additive manufacturing. This model was organized through causal loop and stock-flow diagrams with thirteen supply chain-related variables, covering the supplier, manufacturer, and core manufacturer distributor. Variables such as production time and product inventory levels were considered. Additionally, Gao and Ma (2020) constructed and analyzed the supply chain of manufacturing companies undergoing the service transformation using system dynamics simulation. Subsequently, they investigated the bullwhip effect's characteristics in the supply chain's service transformation. Finally, suitable policies for the supply chain were suggested. Using system dynamics modeling, Mangla et al. (2021), mapped the milk supply chain to uncover information flow among different members for higher traceability. Then, they examined the social impacts of blockchain technology in the milk supply chain to establish the necessary social sustainability.

2.3. System dynamics modeling of supply chains in specific industries

This group uses system dynamics to model and improve supply chains, focusing on specific industries. Mohammadi et al. (2022) developed a dynamic simulation model for the steel supply chain, considering complexities and interactions. This study considered four steel supply chain levels: concentrate, pellet, sponge iron, and steel. The grade and tonnage of iron ore, iron ore supply constraints, production costs, and final profit were the variables examined in this model. Alamerew and Brissaud (2020) that presents a model to represent a complex reverse logistics system for product recovery using a system dynamics approach. They considered costs, revenue, and strategic and regulatory decisions for dynamic modeling.

Additionally, the main enablers and challenges for recovery were presented. Finally, suitable strategies for improving this logistics system were provided. Olivares-Aguila and ElMaraghy (2021) introduced a system dynamics framework to observe supply chain behavior and evaluate the effects of disruptions. The effects of disruptions on service levels, costs, profits, and supply chain inventory levels were analyzed. The framework and findings were used to define policies and support decision-making related to supply chain design. Elyasi and Teimoury (2023) considered the Iranian rice supply chain a system and modeled economic sustainability using system dynamics. They used the soft systems methodology, critical systems heuristic, and interactive planning methodology to define social and environmental sustainability. Finally, they presented seven implementable policies for supply chain managers to achieve sustainability in this supply chain.

Table 2 outlines the objectives, methods, main findings, and gaps of each study to clearly highlight the position and contribution of the present research in addressing existing gaps.

Table 2. Summary of previous studies and identified gaps

Study	Objective	Methods	Key Findings	Identified Gaps
Özbayrak et al. (2007)	Model dynamic behavior of supply chains	System dynamics modeling	Highlighted internal factory-level dynamics	Limited to single-factory analysis without multi-level supply chain context
Ghadge et al. (2020)	Analyze Industry 4.0's impact on supply chains	System dynamics with barriers analysis	Developed a framework for Industry 4.0 implementation	Lacks empirical testing in specific industries like steel
Rebs et al. (2019)	Sustainable supply chain management	System thinking approach with sustainability criteria	Established macro and micro sustainability analysis	Limited focus on long-term economic impacts of Industry 4.0
Nuñez Rodriguez et al. (2021)	Assess additive manufacturing in supply chains	Causal loop diagrams and stock-flow	Demonstrated supply chain behavior with disruptive technologies	Specific to additive manufacturing without insights into traditional industries
Gao and Ma (2020)	Service transformation in manufacturing supply chains	System dynamics with bullwhip effect analysis	Explored effects on service-oriented transformations	No exploration of technology
Alamerew and Brissaud (2020)	Reverse logistics for product recovery	System dynamics modeling for sustainability	Developed policies for logistics recovery systems	Does not address supply chains
Mohammadi et al. (2022)	Steel supply chain dynamics for Iran	System dynamics	Investigated multi-level steel supply chain in Iran	Limited to economic factors; lacks broader Industry 4.0 technology implications
Olivares-Aguila and ElMaraghy (2021)	System dynamics for supply chain design	Defined policies for resilience against disruptions	Disruptions in supply chain systems	Limited to single-factory analysis without multi-level supply chain context

The reviewed literature demonstrates the valuable role of system dynamics in modeling diverse supply chain factors, particularly in the context of Industry 4.0. These studies effectively simulate complex variables related to production rates, sustainability, and resilience within specific industries. However, many tend to concentrate primarily on economic factors, limiting their generalizability and applicability across different contexts. Moreover, there is a pressing need for longitudinal assessments that explore the long-term effects of emerging technologies, such as those associated with Industry 4.0, on supply chains.

Despite advancements in this area, examining macro-level supply chain policies using a system dynamics approach remains a relatively underexplored topic. Our research aims to innovate by analyzing key variables, including export and import rates, production rates, capacity development costs, capacity creation rates, depreciation rates, product accumulation, product demand, and profit margins across a multi-level supply chain. This comprehensive examination will enhance the understanding of the Iranian steel supply chain dynamics and shed light on the broader implications of Industry 4.0 adoption in similar contexts.

3. Method

Developing a suitable framework that allows for the evaluation and analysis of decisions, policies, and various scenarios of a multi-level supply chain requires considering a wide range of variables and relationships affecting the various factors of this supply chain. Therefore, choosing a suitable approach to model this issue is very important. In order to select a suitable approach, two main criteria were considered:

(1) First, our approach should be holistic and consider the dynamics of the supply chain as a coherent whole.

- Second, due to the large number of variables affecting this issue, the chosen approach should be suitable for comprehensive policy analysis.

Therefore, given that system dynamics is a powerful approach for analyzing complex and dynamic systems, this approach was used to model the problem.

System dynamics theory: System dynamics was first introduced by Forrester to identify the dynamics and structure of complex systems. This approach analyzes and examines complex dynamic social, economic, and managerial systems through simulation and provides suggestions for improvement. System dynamics helps us to examine issues from a systemic and overall perspective rather than identifying and defining each issue in detail.

System dynamics modeling is a process that includes various stages, such as defining and identifying the problem, defining the problem variables, defining the model boundaries, defining the model structure, defining mathematical relationships, running and validating the model, and designing and conducting Policies. All modeling issues begin with a real-world problem and end with designing and implementing policies to solve this problem. The stages of this method are shown in Figure 5 (Sterman, 2000; Mashayekhi and Ghili, 2010).

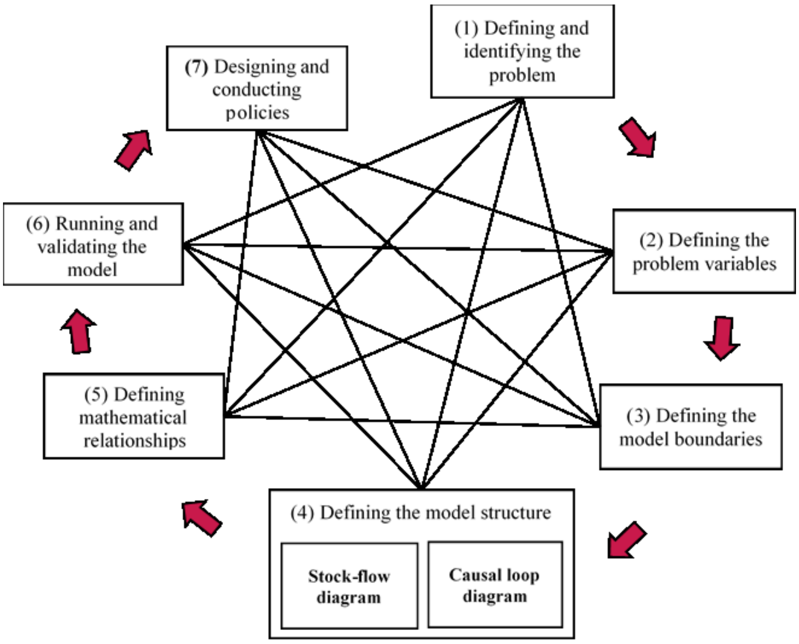

Figure 5. The stages of modeling by the systems dynamics method (Sterman, 2000 and Mashayekhi and Ghili, 2010).

In order to collect data for this research, 21 experts were involved, selected from managers and specialists of industrial complexes, including National Iranian Steel Company, Mobarakeh Steel Company, Alloy Steel Company, Chadormalu Mine, Arfa Steel Company, Golgohar Mine, Jahan Steel Company, Jalal'abad Iron Ore Mine, Zarand Steel Company, and Sanie Kavah Steel. This study used judgmental and snowball sampling methods to select experts. These methods, focused on gathering in-depth information from specialists, helped identify 21 experts for the research process. Field visits to steel production plants and interviews with managers and specialists further enabled the collection of expert insights and practical knowledge. Additionally, data has been obtained from relevant official sources, including the Iran National Steel Company and the Iran Statistics Center to complete the information.

4. Results

In this section, the author proceeds according to the steps outlined in Figure 5 and implements the seven main steps.

4.1. Defining and identifying the problem

Defining and identifying the problem is divided into two parts. The first part involves identifying the main problem regarding the macro policies of multi-level supply chains. The second part concerns identifying the case study that will be used to validate the model.

4.2. Identifying the problem

To identify the factors affecting the macro policies of multi-level supply chains and the variables influencing the formation of causal loop diagrams and stock-flow diagrams and to provide solutions and policies for improving current trends, a proper definition of the problem must first be provided. To this end, semi-structured interviews were conducted with research experts to discover and more accurately identify the system. The purpose and approach of systems dynamics modeling were briefly explained at the beginning of each interview. Then, discussions were held regarding the factors affecting the macro policies of the supply chain, the behavior of key variables over time, and the identification of the causes of these behaviors, variables influencing the formation of causal loops, and dynamic hypotheses, which include identifying how the interacting variables create behavior. Finally, solutions and policies for improving macro supply chain policies were presented.

4.2.1. Reference diagrams

In order to validate the model and conduct experiments, a case study must be selected. In order to examine the suitability of this case study for the developed model, reference diagrams must be drawn. Reference diagrams show the behavioral pattern of the model and lead to a better understanding of the important variables in the modeling process. The reference diagrams of our research include Figure 6 to 8.

Iran's steel production has increased from 30,000 tons in 1971 to over 30 million tons in 2023. The trend of steel production in Iran has almost always been upward in the years after the 1979 revolution. This growth trend is logical since the steel industry has always been one of Iran's major development goals. Considering that Iran's nominal steel production capacity is much higher than its actual production (about 60 million tons), it is predicted that the upward trend of Iran's steel production growth will continue in the coming years. Figure 6 shows the growth of Iran's steel production in recent years.

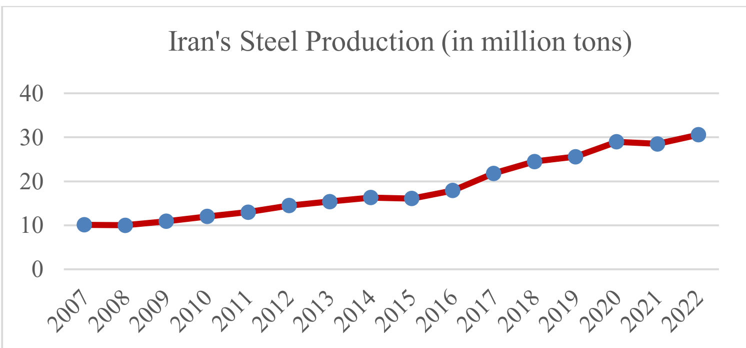

Figure 6. Steel Iran's Crude Steel Production from 2007 to 2022

The amount of iron ore extracted from Iran's mines has consistently shown an upward trend in recent years. Given the establishment of industrial units and steel production, the increase in iron ore extraction is natural. Figure 7 shows the growth trend of iron ore extraction in Iran in recent years.

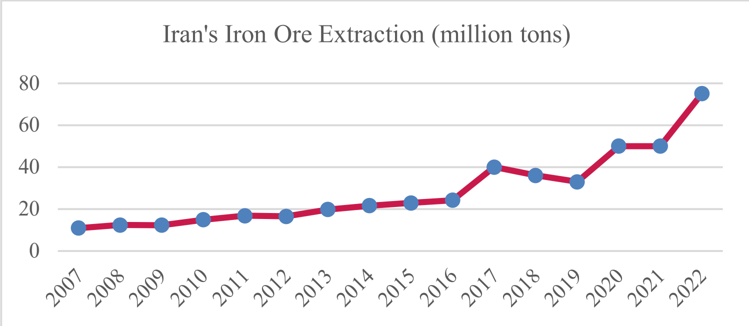

Figure 7. The amount of iron ore extracted between 2007 and 2022

As seen in Figure 8, Iran's steel exports have increased continuously from 2007 to 2022. This increase is due to factors such as the growth of Iran's steel production, the increase in global steel prices, and the improvement of transportation infrastructure. In 2022, Iran ranked ninth globally with 24.7 million tons of steel exports. Most of Iran's steel exports go to countries such as China, India, Turkey, Iraq, and Afghanistan.

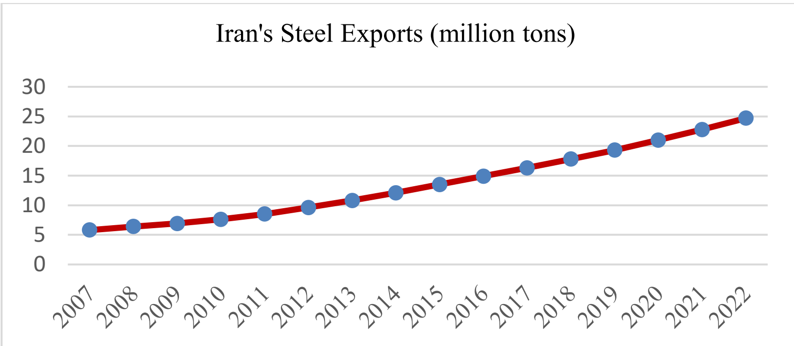

Figure 8. Iran's Steel Exports from 2007 to 2022

Based on Figure 8, the overall trend of the steel supply chain has shown an upward trajectory in most official statistical indicators over the past years. However, in some years, fluctuations in these diagrams can be observed due to the adoption and implementation of certain policies or the occurrence of specific events. By examining the temporal changes in Iran's steel production, iron ore production, and steel exports over the past decade, and considering that Iran's nominal steel production capacity significantly exceeds its actual production, and there are restrictions on the import and export of raw materials, intermediate products, and final products at all levels of this supply chain, a systems dynamics approach can be used to evaluate macro-level import and export policies.

4.3. Defining the problem variables

The next step in systems dynamics modeling is identifying the influential variables of the model. For this purpose, the content validity index was used to validate the model variables. This stage is one of the most important steps in systems dynamics modeling because the fundamental basis of causal loop diagrams and stock-flow models is the influential variables of the model. These variables are identified based on the research objectives, questions, and dynamic assumptions within the model's boundaries.

In this research, after a systematic review of the literature and conducting in-depth semi-structured interviews, an initial list of research variables and their relationships was identified, and based on this, a causal loop diagram and a stock-flow diagram were designed. Then, to ensure the validity of the identified variables, they were tested using a questionnaire based on the content validity index (CVI) assessment. This index determines the necessity of using each variable in the modeling process. The content validity index was first used Waltz and Bausell (1981). In using this index, research experts specify the relevance of each variable based on a four-part scale. Experts rate the relevance of each index according to their personal opinion, from 1 (Not Relevant), 2 (Item Needs Some Revision), 3 (Relevant but Needs Minor Revision), to 4 (Very Relevant). Finally, the content validity index for each variable is calculated as follows:

$$\text{CVI} = \frac{Number\ of\ experts\ rating\ the\ variable\ as\ 3\ or\ 4}{Total\ number} \tag{1}$$

The minimum acceptable value for the CVI is 0.79, and if the CVI for a variable is less than 0.79, that variable should be eliminated. The results of the test are presented in Table 3.

Table 3. Results of CVI Test

Number	Variable Name	Number of experts who rated the variable as 3 or 4	CVI
1	Development Costs	21	1
2	Production Capacity	21	1
3	Capacity Production Rate	21	1
4	Depreciation Rate	19	0.9
5	Product Accumulation	18	0.86
6	Export Rate	21	1
7	Import Rate	20	1
8	Over Demand	19	0.9
9	Production Rate	21	1
10	Demand	21	1
11	Demand Increase	21	1
12	Selling Rate	21	1
13	Profit	21	1
14	Total Profit	21	1

4.4. Defining the model boundaries

Every research should have a specific scope regarding time, place, and subject. Defining these boundaries ensures that the research results are reliable in application. The subject scope of this research is the structure of a multi-level supply chain, and the spatial scope is the steel supply chain in Iran.

In order to collect the data used in this research, sources, and data related to the Iranian steel supply chain from 2007 to 2022 have been used. The reason for this choice is that many important historical events of this supply chain have occurred during this period, and their effects have been observable, resulting in the possibility of analyzing the model's behavior. Additionally, a 15-year time frame is long enough to observe the effects of decision results. The temporal scope of the research covers the next ten years.

4.5. Defining the model structure

In this research, after identifying the important variables and parameters affecting the macro-level policies of the multi-level supply chain, drawing reference diagrams, and identifying important trends and patterns of the supply chain, the dynamic model of the problem is formulated. The primary stage in using systems dynamics modeling is to try to identify and understand the feedback loops of the system.

One of the existing methods for this is to draw causal loop diagrams. This stage is the first step in the operational process of systems dynamics modeling. The next stage in this modeling is to draw a stock-flow diagram. These diagrams aim is to show the relationships between the model variables.

4.5.1. Drawing the causal loop diagram of the model

In order to draw the causal loop diagram of the model, the relationships from budget allocation to reaching the final profit have been shown in a diagram. This diagram shows only one level of the multi-level supply chain; the other levels operate according to the same diagram (Figure 9).

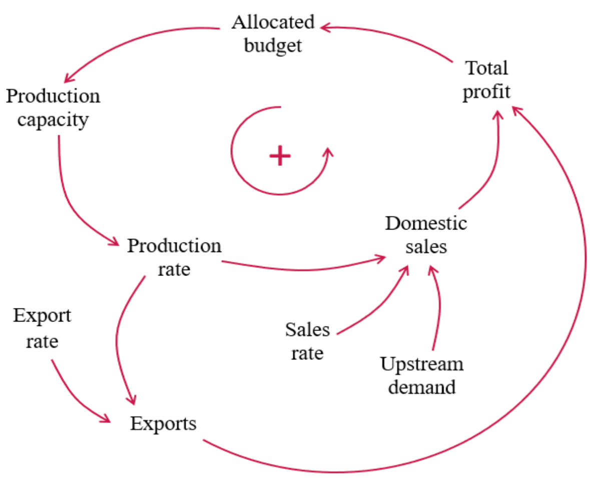

Figure 9. Causal loop diagram from budget allocation to profit achievement

This diagram invests the total profit obtained in increasing production capacity. Increasing production capacity leads to an increase in production rate, and with an increase in sales and exports, the total profit increases, and this process continues as a positive cycle. In the next diagram, five levels of the steel supply chain are visible (Figure 10). This diagram shows the relationship between the different levels of the multi-level supply chain.

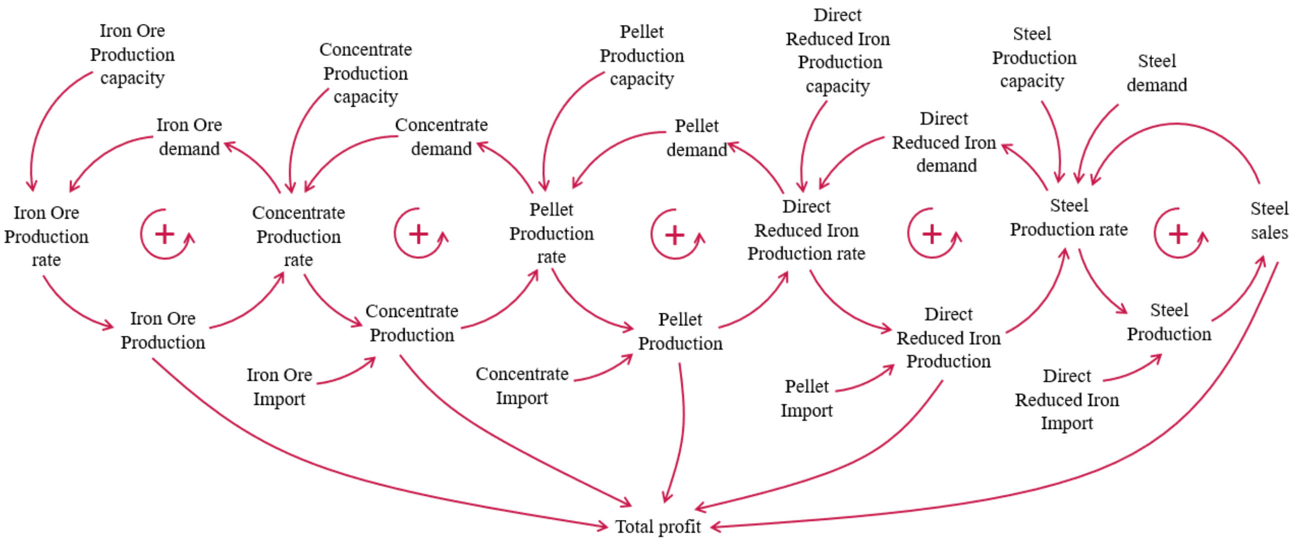

Figure 10. Causal loop diagram of the relationship between different parts of a multi-level supply chain

This diagram shows that the production capacity and production rate of upstream products influence the demand for downstream products. The diagram also illustrates the impact of imports within the supply chain. Each level exhibits a positive reinforcing cycle.

4.5.2. Drawing the stock-flow diagram

In order to draw the stock-flow diagram, all system variables must be identified, and the model boundaries must be clearly defined. State variables represent the accumulations within the system that indicate its current state, and the information from these variables informs decision-making and actions. Flow variables represent the rates of change of the state variables.

The stock-flow model was created using AnyLogic software. For simplicity, some variables are abbreviated, as shown in Table 4.

Table 4. Abbreviation of supply chain level names

Abbreviation	IO	IC	IP	DRI	CS
Word	Iron Ore	Iron Concentrate	Iron Pellet	ect Reduced Iron	Crude Steel

Figure 11 shows the stock-flow diagram for the first level of the multi-level steel supply chain, specifically for iron ore. This diagram includes as many variables as possible that impact the macro-level policies of this sector.

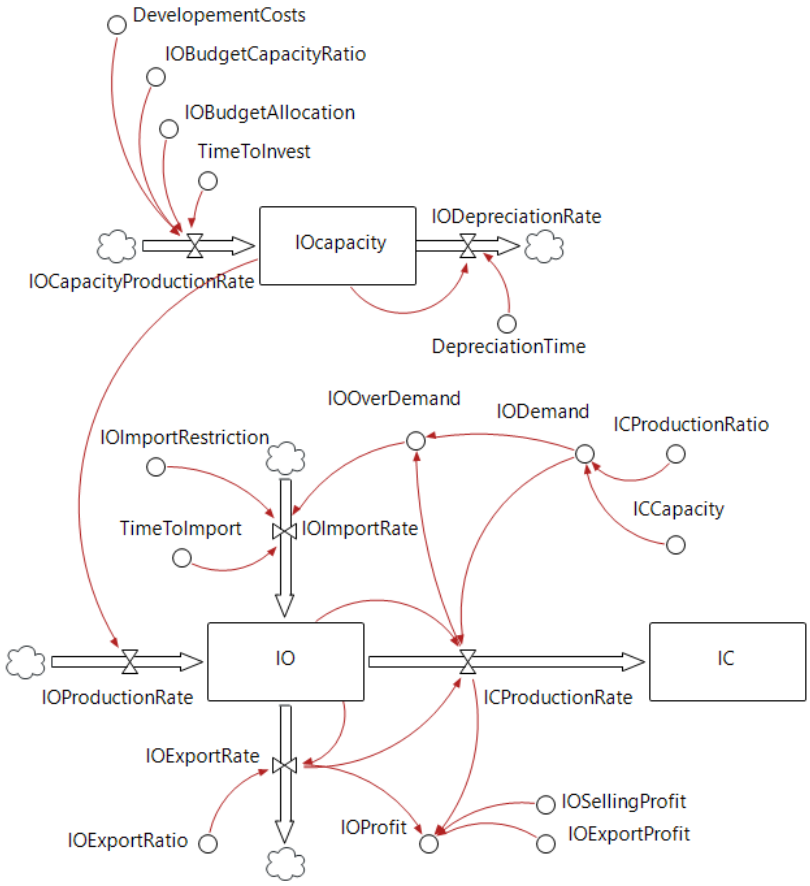

Figure 11. Stock-flow diagram of one level of a multi-level steel supply chain

In this diagram, two state variables are considered for the iron ore sector: the production capacity of iron ore (IOCapacity) and the accumulation of iron ore production (IO). The relationships between these variables and their impact on the system will be explained in detail. Figure 12 expands on the previous diagram by including all levels of the supply chain and their interrelationships. It presents the complete stock-flow diagram for a five-level steel supply chain.

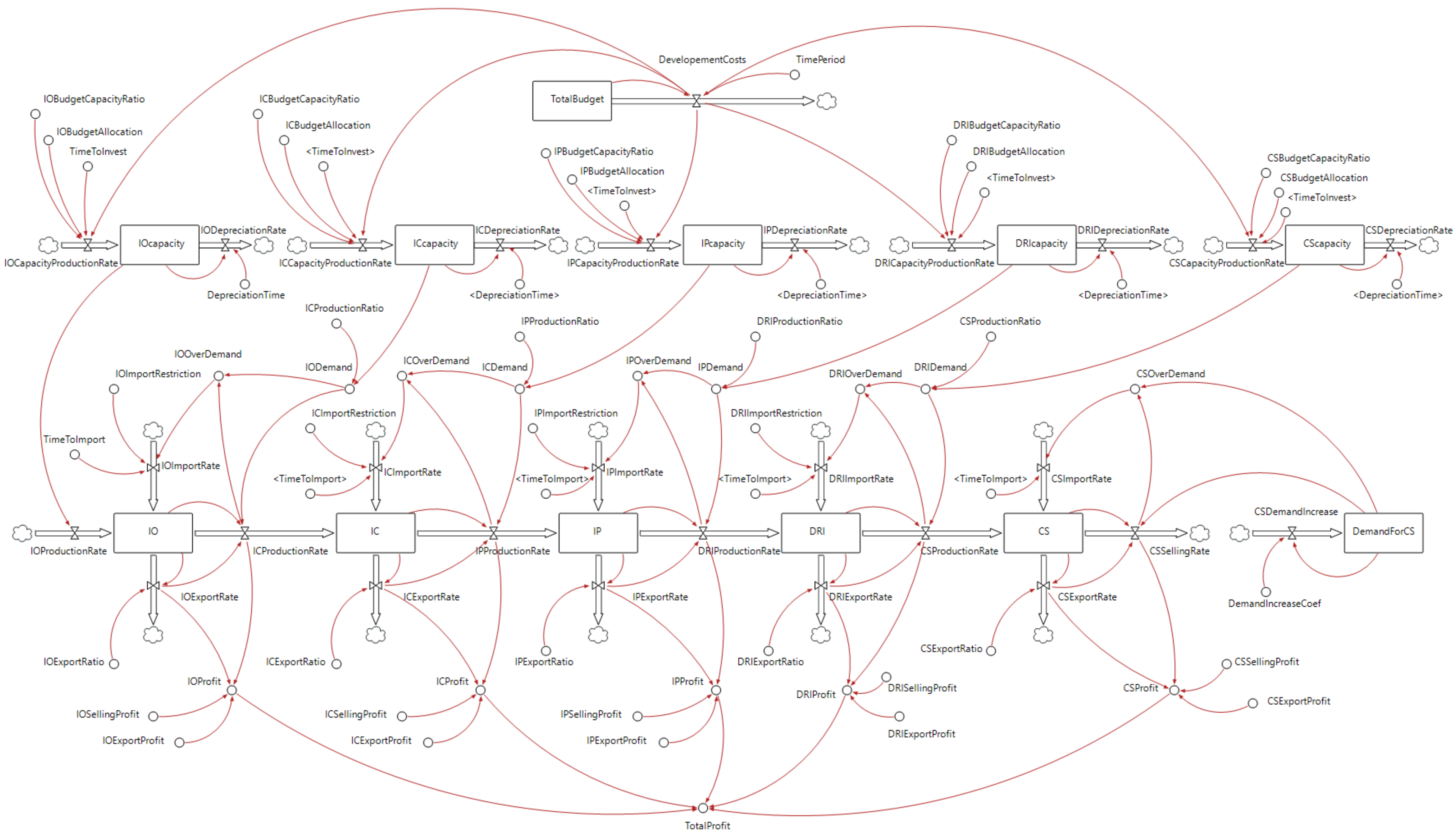

Figure 12. Stock-flow diagram of the problem for a five-level multi-level steel supply chain

DOI: 10.22067/JSTINP.2024.89351.1115

The next section will describe the mathematical relationships between the variables.

4.6. Defining mathematical relationships

At this stage, the mathematical relationships between the model variables are examined. These relationships are consistent across all five levels of the steel supply chain.

$$\text{Development Costs} = \text{Total Budget/Time Period} \tag{2}$$

The development cost of production capacity is obtained by dividing the total allocated budget by the time required to consume this cost.

$$\text{IO Capacity} = \text{INTEG (IO Capacity Production Rate - IO Depreciation Rate)} \tag{3}$$

The accumulation of iron ore capacity (IO) is equal to the integral of the production capacity creation rate minus the depreciation rate of production units. For the next levels of the supply chain, namely concentrate production (IC), pellet production (IP), direct reduced iron (DRI), and crude steel (CS), the calculations are done similarly. The initial values of these accumulations should also be determined based on the documents.

$$\text{IO Capacity Production Rate} = \text{(IO Budget Allocation * Development Costs) /} \\ \text{(IO Budget Capacity Ratio * Time to Invest)} \tag{4}$$

In order to obtain the iron ore capacity production rate, the percentage of the total development budget of the steel sector allocated to iron ore extraction must be multiplied by the total development costs. It should also be considered how much is needed to create one million tons of iron ore extraction capacity and the investment period..

$$\text{IO Depreciation Rate} = \text{IO Capacity / Depreciation Time} \tag{5}$$

To calculate the depreciation rate, the accumulated iron ore capacity must be divided by its average depreciation time.

$$\text{IO} = \text{INTEG (IO Import Rate + IO Production Rate - IO Export Rate - IC Production Rate)} \tag{6}$$

The accumulation of iron ore is calculated by integrating the sum of the inflow rates (i.e., the import rate of iron ore and the production rate of iron ore) minus the outflow rates (i.e., the export rate and the production rate of the next level product (concentrate)). The initial values of these accumulations should also be determined based on the documents.

$$\text{IO Export Rate} = \text{IO * IO Export Ratio} \tag{7}$$

The export rate of iron ore is considered based on the policies of steel sector managers. In general, a large part of iron ore production should be used domestically to produce the next steel products in the supply chain, and all iron ore production should not be exported. Even though the profit from exporting iron ore may sometimes be higher than the that selling to domestic factories, legal restrictions must still be complied with.

CS Import Rate = Min (Import Restriction, IO Over Demand/Time to Import) (8)

The import rate of iron ore is determined based on the import restrictions. Given the domestic iron ore mineral resources, importing this product is not logical. Also, excess demand should affect iron ore imports. Therefore, if the demand for upstream units is higher than the iron ore extraction capacity, imports will be possible up to a certain limit.

IO Over Demand = Max (0, IO Demand - IC Production Rate) (9)

Excess demand for iron ore is obtained by comparing the demand for iron ore and the production rate of the upstream product of the supply chain (concentrate). If this value is negative, the excess demand becomes zero, and there will be no imports.

IO Production Rate = IO Capacity (10)

IC Production Rate = Min (IO – IO Export Rate, IO Demand) (11)

The iron ore extraction rate is equal to the accumulated iron ore capacity. This rate for the production of upstream products (concentrate) is equal to the demand for the production of the downstream product. Suppose the amount of the downstream product accumulation minus the amount exported is less than the domestic market demand. In that case, the production rate of the upstream product will be equal to the amount of the downstream product inventory in the market.

IO Demand = IC Capacity / IC Production Rate (12)

The demand for iron ore is determined by the upstream product, which is the concentrate and is obtained by dividing the production capacity of the upstream product by the ratio of concentrate production from one ton of iron ore.

CS Demand Increase = Demand for CS * Demand Increase Coefficient (13)

The rate of increase in the demand for crude steel (CS) is calculated by multiplying the existing demand inventory by the annual demand increase coefficient. The annual demand increase coefficient is determined based on the supply and demand of crude steel over the past ten years.

CS Selling Rate = Min (CS - CS Export Rate, Demand for CS) (14)

The sales rate of crude steel is calculated by comparing the demand for crude steel and the amount of crude steel inventory minus its export amount. If the demand for crude steel is less than its existing inventory, the sales rate will be equal to the demand, and if the demand is greater than the existing inventory, the sales will be equal to the inventory.

IO Profit = (IC Production Rate * IO Selling Profit) + (IO Export Rate * IO Export Profit) (15)

Total Profit = IO Profit + IC Profit + IP Profit + DRI Profit + CS Profit (16)

The profit from iron ore production includes domestic sales and exports. The total profit of the products is obtained by summing the profits from each level in Equation 16.

4.7. Running and validation the model

4.7.1. System warm-up time

Since simulation models do not have the same initial conditions as those in a real-world problem, a specific time is determined for system warm-up. In order to calculate the system warm-up time, it is recommended to plot a specific graph of the status of one or more system variables, and the approximate warm-up time can be determined from this graph. The system warm-up time is the time it takes for the simulated system to reach a relatively stable state. For this problem, to determine the warm-up time of the system, a graph was plotted to examine the behavior of the state variables of the production rate of three levels of the supply chain (pellet, direct reduced iron, and crude steel) over ten years (Figure 13).

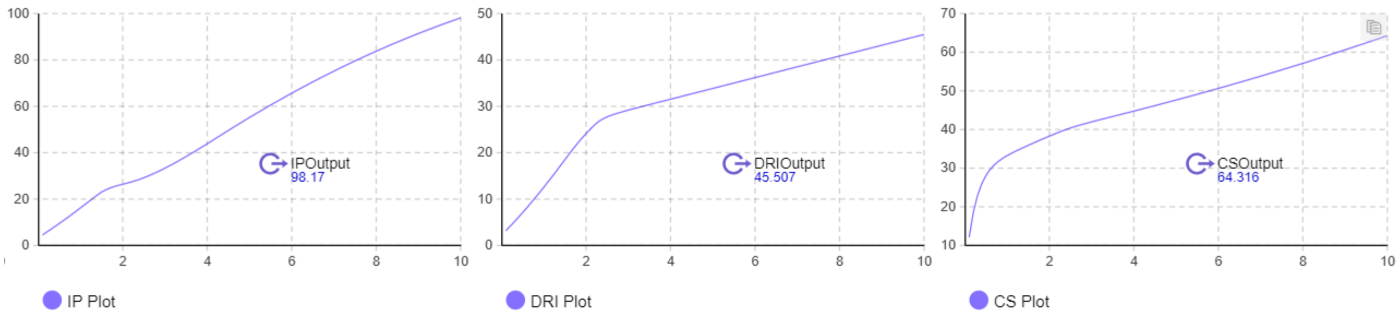

Figure 13. Analysis of variable behavior to determine system warm-up time

After examining these three diagrams, a warm-up time of two years was considered. All three diagrams reached a relatively stable state after about two years. The duration of the simulation run, excluding the system warm-up time, is 10 years. Therefore, the authors simulate for 12 years.

4.7.2. Model validation

In order to ensure that the model provides a sufficiently acceptable representation of the actual system, a validation process is carried out. In modeling each level of this supply chain, our effort has been to ensure that the outputs are consistent with the real-world problem environment and that the validation process has been carried out continuously. In this article also used several tests to check the validity of the model:

4.7.2.1. Boundary condition test

This test checks whether the model exhibits expected behavior under extreme conditions. These extreme conditions may not have occurred in the real world. In order to examine this test in this research, several state variables were examined regarding changes in the factors affecting their input rate. The variable that is being measured is the profit variable.

In this way, the authors want to examine if the authors significantly reduced the total budget of the supply chain by one thousandth from the second year. Then, what would be the trend of the total profit of the supply chain? As expected, the annual budget reduction of the supply chain shows its effect in all parts of the supply chain. For example, in Figure 14, changes in the budget reduction on iron ore production capacity can be seen. In cases where the annual budget is exhausted, the diagram becomes stepped.

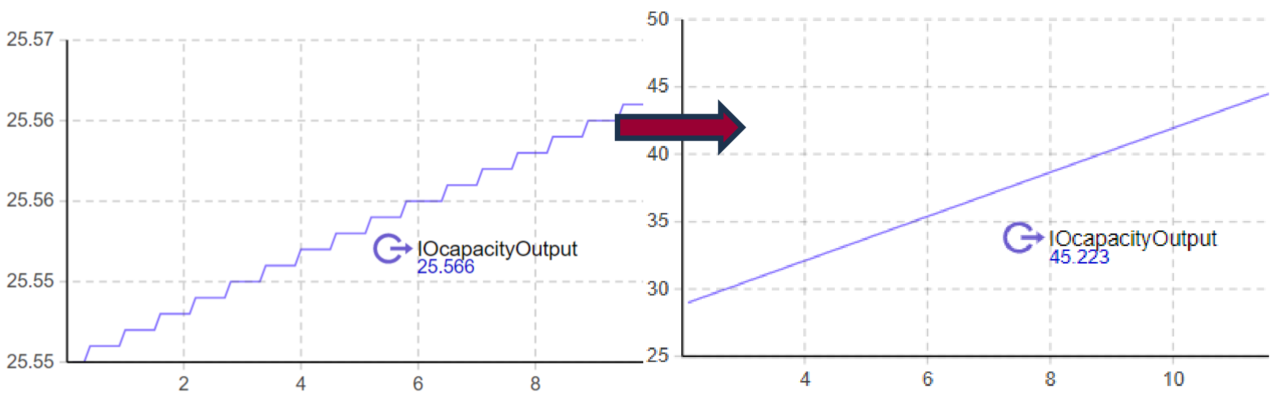

Figure 14. Examination of the behavior of the iron ore production capacity variable under extreme conditions

Ultimately, this stepped effect, after affecting the production rate and the state variable of the production amount of each level, affects the total profit (Figure 15).

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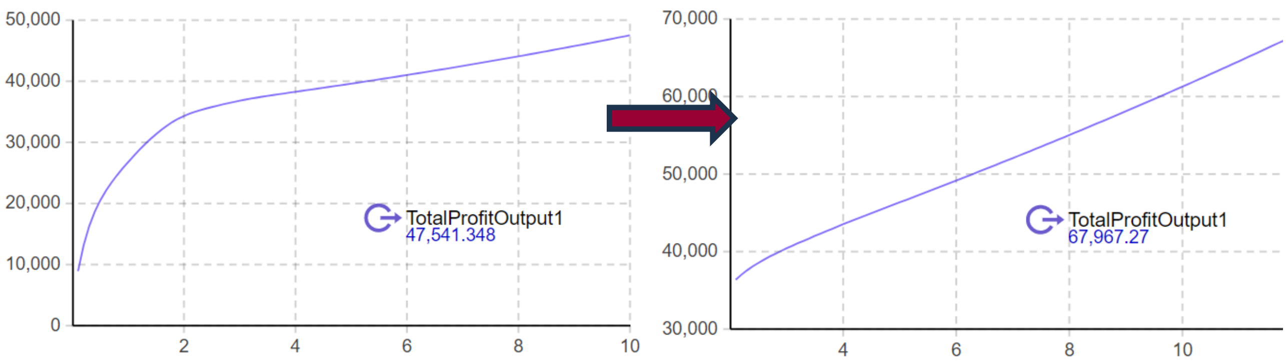

Figure 15. Analysis of the behavior of the total profit variable under extreme conditions

4.7.2.2. Reproduction behavior test

This test examines whether the model's initial conditions are equal to the conditions of the real world. If this match exists, the model can produce information similar to real systems. In order to examine this test, this article used reference diagrams to compare them with the diagrams produced by the model and measure their conformity. For this purpose, before simulating the future, the authors ran the model with data from the past years to compare its results with reality. According to Figure 16, the actual data of Iran's steel production from 2007 to 2022 is shown as a blue graph, and the values received from the simulation model are shown as a red graph. According to this diagram, the simulated values and the actual values have a reasonably good match.

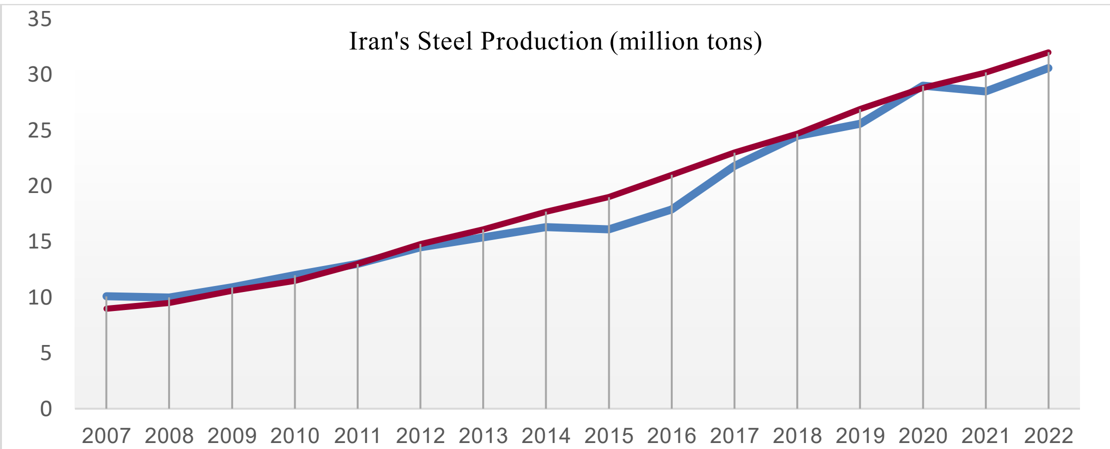

Figure 16. Comparison of Iran's crude steel production in reality and simulation

Also, in Figure 17, the actual data of Iran's iron ore extraction from 2007 to 2022 is shown as a blue graph, and the values received from the simulation model are shown as a red graph. This diagram also shows a relative match between the simulated and actual values.

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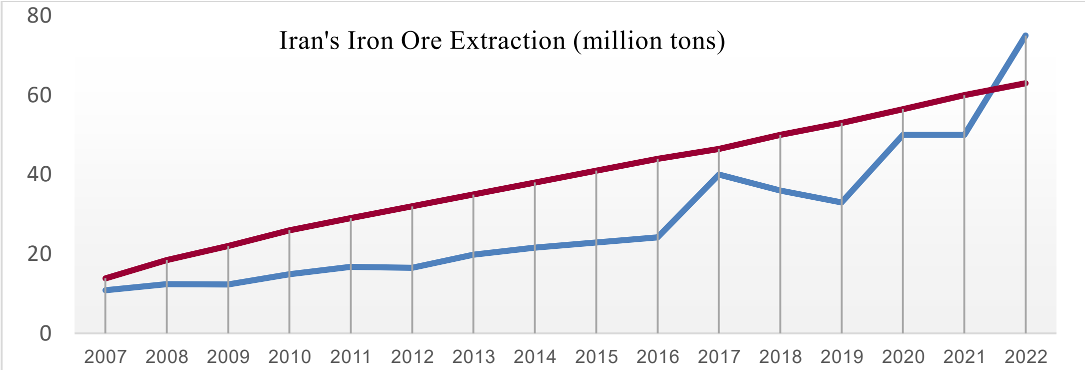

Figure 17. Comparison of Iran's iron ore extraction in reality and simulation

Another state variable examined in this section is the amount of Iran's steel exports. According to Figure 18, the actual data of Iran's steel exports from 2007 to 2022 is shown as a blue graph, and the values received from the simulation model are shown as a red graph. This diagram also shows a relative match between the simulated and actual values.

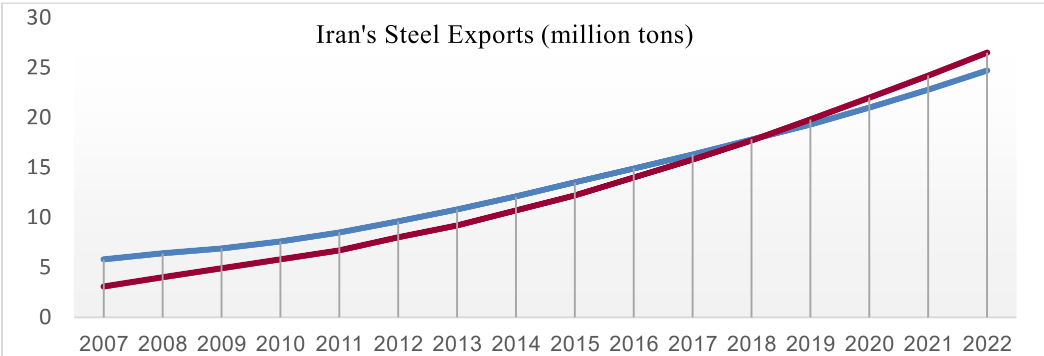

Figure 18. Comparison of Iran's steel exports in reality and simulation

4.7.2.3. Statistical validation methods

Important indicators that can be used to determine the degree of closeness of the simulated values to the actual values in the validation test of the system dynamics model and were used in this research include Root Mean Square Error (RMSE), Root Mean Square Percentage Error (RMSPE), Theil's Inequality Coefficient (U), and Theil's error decomposition. The statistical tests designed are shown in Table 5. For calculations, the base year was considered to be 2007.

Table 5. Statistical validation of the dynamic model

Variable	Root Mean Square Error (RMSE)	Root Mean Square Percentage Error (RMSPE)	Theil's Inequality Coefficient (U)	Theil's Error Decomposition		
				Correlation error	Variance error	Mean error
	The lower, the better	Value between zero and one hundred	Value between zero and one	The sum equals one		
IO Production	108.11	0.17	0.12	0.63	0.08	0.03
CS Production	522.18	0.17	0.12	0.63	0.08	0.03
CS Exports	4880.76	0.25	0.45	0.36	0.32	0.06
CS Sales	12920	0.18	0.11	0.63	0.01	0.10
Total Profit	10.62	0.30	0.03	0.38	0.31	0.03

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The smaller the Theil index and the closer it is to zero, the closer the simulated numbers are to the actual numbers. Based on the investigations conducted in Table 5, the variables of the simulation model are close to the actual numbers, and the model's behavior, in terms of statistics, is reasonably close to the actual behaviors of the key variables of the problem. Therefore, the authors can run the model and receive the necessary outputs based on the policies. Model Execution

The model was run in AnyLogic software. The diagram of some of the model's accumulations and the total profit variable after running the model for 10 years is shown in Figure 19 and Figure 20.

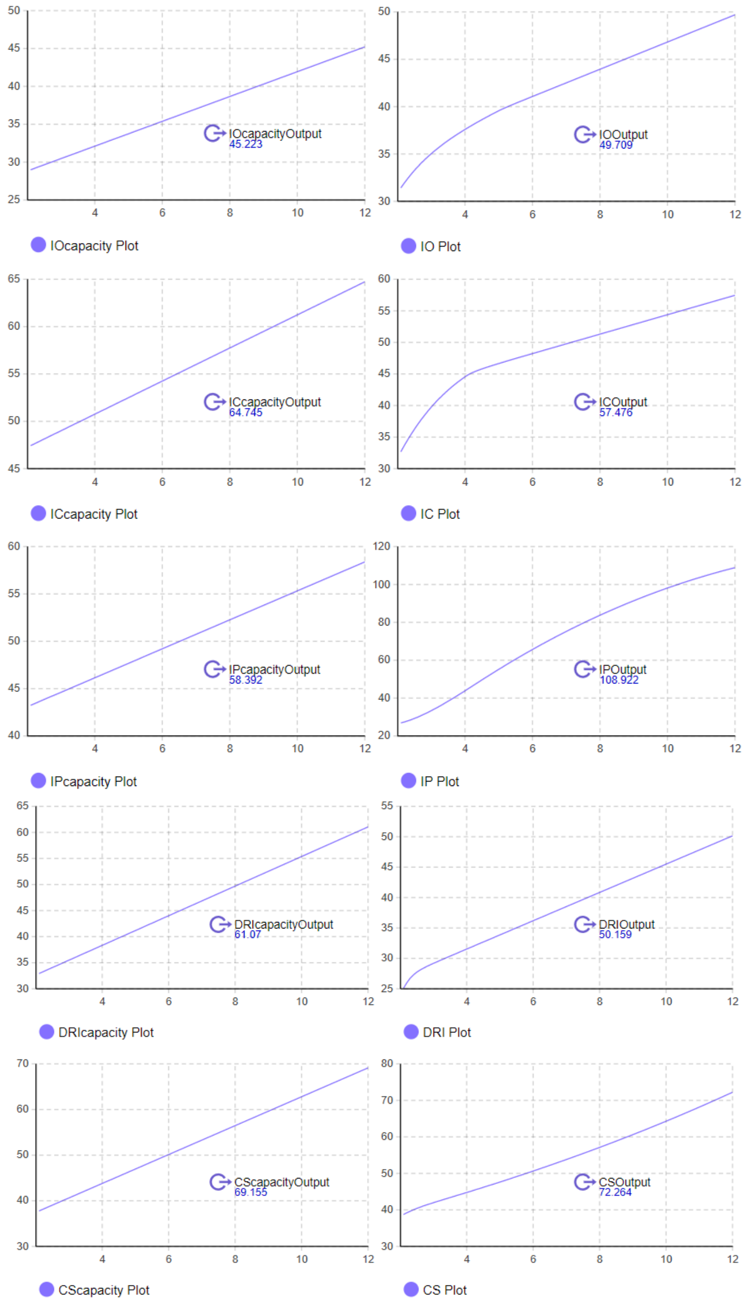


Figure 19. Model execution (Capacity and production of 5 levels of the supply chain)

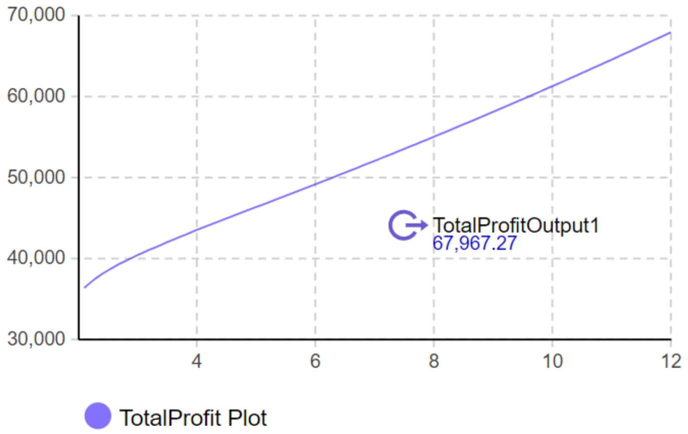


Figure 20. Model execution (Total profit)

4.8. Designing and conducting policies

The model's sensitivity to changes in some variables indicates the importance of those variables. Therefore, after running the model, the authors identified the more sensitive variables and tracked the effects of these changes made in the model by making changes to them. Since this research is looking to examine the macro policies of the supply chain, the authors select macro variables for sensitivity analysis. These variables are as follows:

Total Budget
Percentage of budget allocation for all five levels of the supply chain (Budget Allocation)
Export limitation for all five levels of the supply chain (Export Ratio)

4.8.1. Sensitivity analysis of total budget allocated to the steel sector

Considering the budget allocated to create the capacity of the steel sector in Iran in the last 15 years, the total budget for the next 15 years is estimated to be 163831 million Tomans. With a 10% increase in the total allocated budget, the graph of changes in total profit will be shown in Figure 21.

Figure 21. Sensitivity analysis of the total profit for an increase in the budget

According to the diagram, the total profit change relative to the budget change is not very significant. Table 6 shows the percentage increase in total profit for an increase in the budget.

Table 6. Percentage increase in total profit for an increase in the budget

Allocated Budget	Percentage Increase	Total Profit	Percentage Increase
163831	-	67967	-
180214	10%	69624	2.43%
196597	10%	71275	2.37%
212980	10%	72901	2.28%

According to Table 6, increasing the budget will not be very profitable for this supply chain under the current conditions. However, focusing on one level of the supply chain to increase the budget may create higher profitability. Therefore, this article will analyze the sensitivity of the budget allocation percentage between different supply chain levels.

4.8.2. Sensitivity analysis of budget allocation to each level of the supply chain

In order to examine and analyze the sensitivity of the model to the percentage of budget allocation to each level of the supply chain, it has been added 8% to the budget allocation of each level, respectively, and 2% from each of the other levels. The results are according to Table 7.

Table 7. Amount of change in total profit for an increase in the budget of each level of the supply chain

Status	IO	IC	IP	DRI	CS	Total Profit	Percentage Increase
Initial State	15%	16%	14%	26%	29%	67967	-
Increase IO budget	23%	14%	12%	24%	27%	66736	-0.181%
Increase IC budget	13%	24%	12%	24%	27%	66669	-0.191%
Increase IP budget	13%	14%	22%	24%	27%	66770	-0.176%
Increase DRI budget	13%	14%	12%	34%	27%	68124	0.002%
Increase CS budget	13%	14%	12%	24%	37%	68293	0.005%
Increase DRI and CS budget	13%	14%	12%	29%	32%	69018	0.015%
Increase DRI and CS budget	11%	12%	10%	32%	35%	69769	0.026%

As shown in the table, only increasing the budget for direct reduced iron and crude steel can increase the overall profitability of the supply chain. The reason for this is the higher price of directly reduced iron and crude steel compared to the products of other levels of the steel supply chain. The more directly reduced iron and crude steel are produced, the more profitable it will be to import their raw materials from abroad and export the product abroad.

4.8.3. Sensitivity analysis of export limits at each level of the supply chain

In order to analyze the sensitivity of the model to export limits at each level of the supply chain, the export limit has been increased according to Table 8 (the initial state is calculated based on IMIDRO).

Table 8. Sensitivity analysis of export limits of each level of the supply chain

Status	IO	IC	IP	DRI	CS	Total Profit	Percentage Increase
Initial State	6.65%	3.86%	1.75%	3.33%	21.5%	67967	-
Increase IO limit	13.3%	3.86%	1.75%	3.33%	21.5%	67879	-
Decrease IO limit	3.32%	3.86%	1.75%	3.33%	21.5%	67911	-
Increase IC limit	6.65%	7.72%	1.75%	3.33%	21.5%	68042	0.001%
Decrease IC limit	6.65%	1.93%	1.75%	3.33%	21.5%	67870	-
Increase IP limit	6.65%	3.86%	3.5%	3.33%	21.5%	68174	0.003%
Decrease IP limit	6.65%	3.86%	0.87%	3.33%	21.5%	67845	-
Increase DRI limit	6.65%	3.86%	1.75%	6.67%	21.5%	68250	0.004%
Decrease DRI limit	6.65%	3.86%	1.75%	1.67%	21.5%	67831	-
Increase CS limit	6.65%	3.86%	1.75%	3.33%	43.0%	76931	0.13%
Decrease CS limit	6.65%	3.86%	1.75%	3.33%	10.7%	64734	-

Based on the results obtained, the export of crude steel is the most profitable part of Iran's steel supply chain. On the other hand, according to the analysis of the previous policy, increasing the budget for crude steel production also leads to higher chain profitability. The simultaneous analysis of these two policies shows that increasing the budget for investment in crude steel production can lead to increased production, and given that there is always the possibility of exporting crude steel, this investment will never fail.

4.9. Investigating the impact of industry 4.0 on the model

Since our model shows the macro level of the supply chain, it is impossible to examine the impact of Industry 4.0 at this level. For this reason, the impact of Industry 4.0 on improving the supply chain must first be calculated with another model that considers the intermediate level of the supply chain and then enters this impact into the dynamic model through a variable. For this reason, we use agent-based simulation for this part, according to Figure 22.

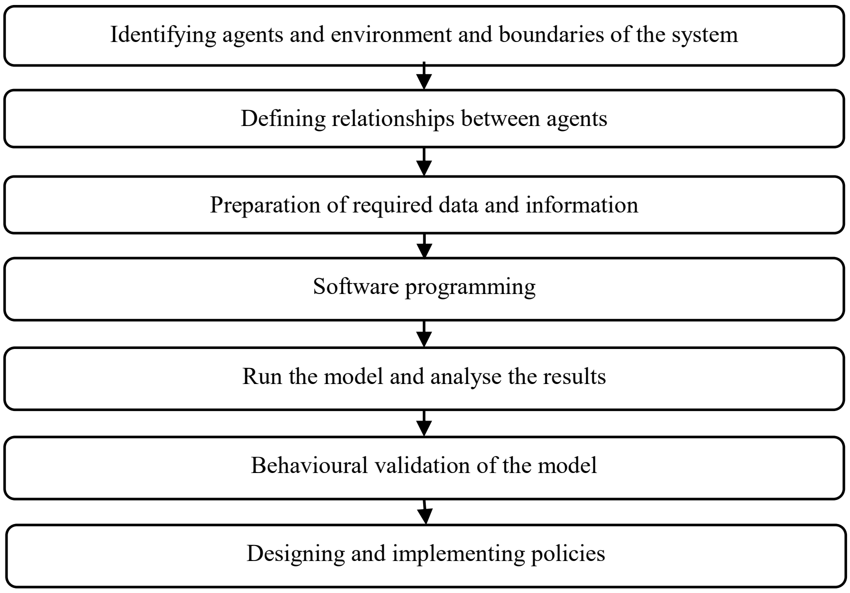


Figure 22. The stages of modeling by the agent-based method (Wang et al., 2021).

According to Figure 23, this article has six agents in this model, which respectively show the six levels of the steel supply chain.

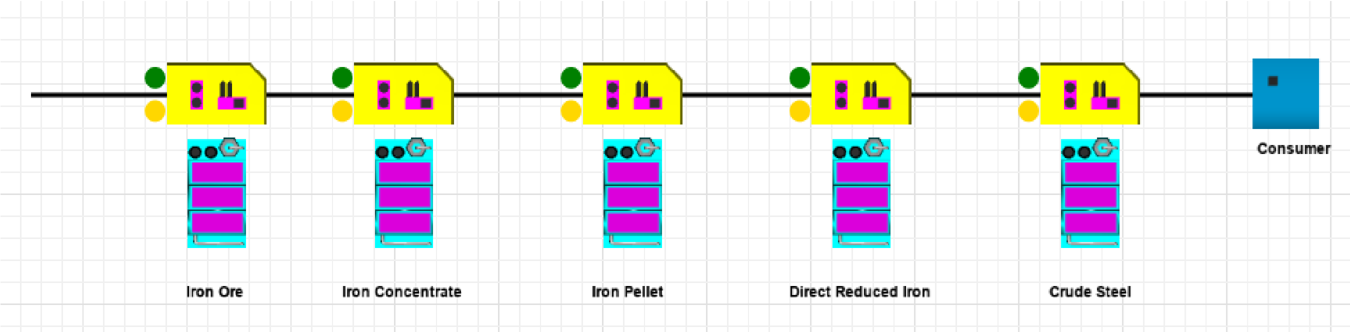


Figure 23. Agents of the levels of Iran's steel supply chain

The variables that were defined in this model in AnyLogic software for agents are as follows:

(2) Production rate
- The utilization rate of production capacity
- Inventory of raw materials
- Inventory of finished goods
- The quantity ordered to the supplier
- Transportation time between two production units
- The distance between two production units
- Customer demand
- Production capacity of each production unit
- Initial stock of raw materials in each production unit
- Minimum inventory level of raw materials

Each agent’s location and production information of all active units of Iran's steel supply chain were introduced into the model as a CSV file.

In order to evaluate the performance of the model and examine how it works, the authors extract a key output. The authors selected the total distance traveled in Iran's steel supply chain and the total time spent to receive products from suppliers (from order to receipt) throughout the supply chain as the influential outputs of the model.

(3) Total distance traveled in the supply chain: This output shows the total distance that raw materials and finished products travel throughout the supply chain during production, transportation, and distribution.
- Total time spent to receive products: This output shows the total time it takes from the time customers receive products.

Examining both distance and time criteria simultaneously can determine the status of the supply chain for us.

Based on the data recorded in the model, the model has been run for ten years (from 1393 to 1402). The results are shown in Table 9.

Table 9. Simulation results of the annual distance traveled and waiting times

Number	Year	Total distance traveled (billion kilometers)	Total waiting times (million hours)
1	1393	220.225	3.1828
2	1394	225.147	3.2594
3	1395	226.657	3.2785
4	1396	227.843	3.2929
5	1397	230.346	3.3357
6	1398	233.478	3.3786
7	1399	235.619	3.3973
8	1400	238.135	3.4534
9	1401	241.476	3.4929
10	1402	243.145	3.5243

These distances are relatively large, indicating that efforts must be made to improve the efficiency of the supply chain. In order to examine policies, the authors will implement cases where the authors can implement Industry 4.0 in the model. Reducing the number of product movements and optimizing transportation routes reduce the distance traveled, saving time and costs. It can increase the competitiveness of Iran's steel supply chain in global markets.

In order to ensure the complete validity of the model, the dataset obtained from the model and the actual Iranian steel supply chain system were compared. Statistics from the Transportation Organization were used to obtain the actual model information in order to validate the model. For this purpose, the Kolmogorov-Smirnov test has been used the Kolmogorov-Smirnov test to measure the normality of the data, and then the analysis of variance and the F-test to determine the similarity of the variances and means of the two datasets. Finally, the T-test was used to examine the difference in means. A summary of the test results is shown in Table 10.

Table 10. Results of statistical tests

Parameter	**Value 1**			**Value 2**	
P-value	0.8436			0.5007	
D	0.139			0.1771	
K	0.4397			0.5602	
Skewness	0.06183			-0.02717	
Source	**DF**	**Sum of Square**	**Mean square**	**F Statistic**	**P-value**
Groups (between groups)	1	9.8	9.8	0.1583	0.6954
Error (within groups)	18	1114.0001	61.8889		
Total	19	1123.8001	59.1474		
Parameter	**Value**				
P-value	0.08859				
t	1.9091				

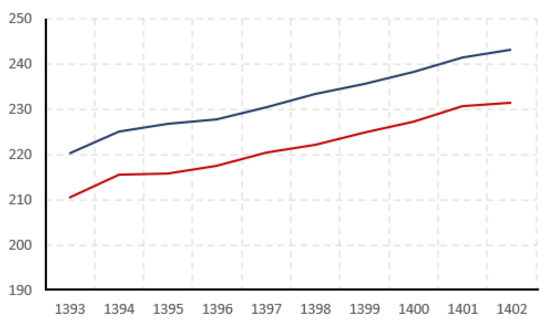
According to the tests, it can be claimed with 95% confidence that there is no significant statistical difference between the real system and the simulation model, and the created model is valid.

Then, this article examines the policies and sensitivity analysis of the supply chain model to changes in key parameters related to Industry 4.0. A policy that the authors can implement in this model by implementing the concepts of Industry 4.0 in Iran's steel supply chain is the horizontal integration of the supply chain. All production units operating at each chain level are somehow integrated by sharing their production on a common cloud platform. In this way, the production units at the next level can obtain the fastest raw materials from this cloud platform. In this case, suppliers and customers are not predetermined, and the nearest supplier is selected based on the distance that can deliver the product to the customer in the shortest time.

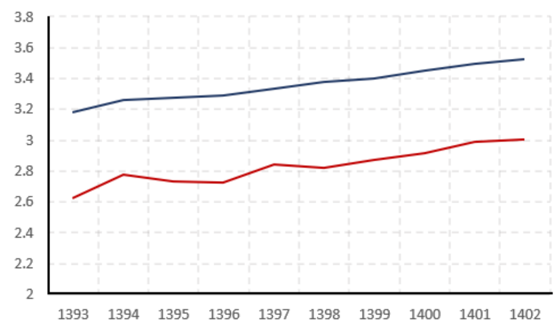
Table 11 shows the model's results before and after implementing the Industry 4.0 policy.Table 11. model results after implementing the Industry 4.0 policy

Number	Year	Total distance traveled (billion kilometers)		Percentage Increase	Total waiting times (million hours)		Percentage Increase
		Before I4.0	After I4.0		Before I4.0	After I4.0	
1	1393	220.225	210.365	4.48	3.1828	2.6248	17.53
2	1394	225.147	215.453	4.31	3.2594	2.7736	14.90
3	1395	226.657	215.756	4.81	3.2785	2.7347	16.59
4	1396	227.843	217.432	4.57	3.2929	2.7258	17.22
5	1397	230.346	220.496	4.28	3.3357	2.8439	14.74
6	1398	233.478	222.214	4.82	3.3786	2.8247	16.39
7	1399	235.619	224.934	4.53	3.3973	2.8736	15.42
8	1400	238.135	227.234	4.58	3.4534	2.9134	15.64
9	1401	241.476	230.763	4.44	3.4929	2.9878	14.46
10	1402	243.145	231.436	4.82	3.5243	3.0069	14.68

Changes in the number of distances traveled and amount of waiting times of the model after implementing the I4.0 policy are shown in Figure 24.



a: Changes in the amount of distances traveled



b: Changes in the amount of waiting times

Figure 24. Changes in the amount of distances traveled and amount of waiting times

The results show that implementing this policy can reduce about 4.5% in the distance traveled and about 15% in waiting times in Iran's steel supply chain.

4.10. Connecting dynamic and agent-based simulations

In order to establish a connection between these two models and create a combined model, it's necessary to first calculate the percentage improvement in supply chain profitability within the agent-based model. The agent-based simulation results show that implementing Industry 4.0 can reduce the distance traveled by 4.5% and waiting times by 15%, so the annual cost savings from this performance improvement must be calculated.

According to information from the National Iranian Steel Company, transportation costs generally account for 15-25% of the total costs in Iran's steel supply chain. The authors assume this cost to be 20%. Therefore, with a 4.5% reduction in transportation costs, it can be estimated that approximately 0.9% of the total supply chain costs will decrease.

This study has used two intermediate variables to establish a connection between the two models (Figure 25).

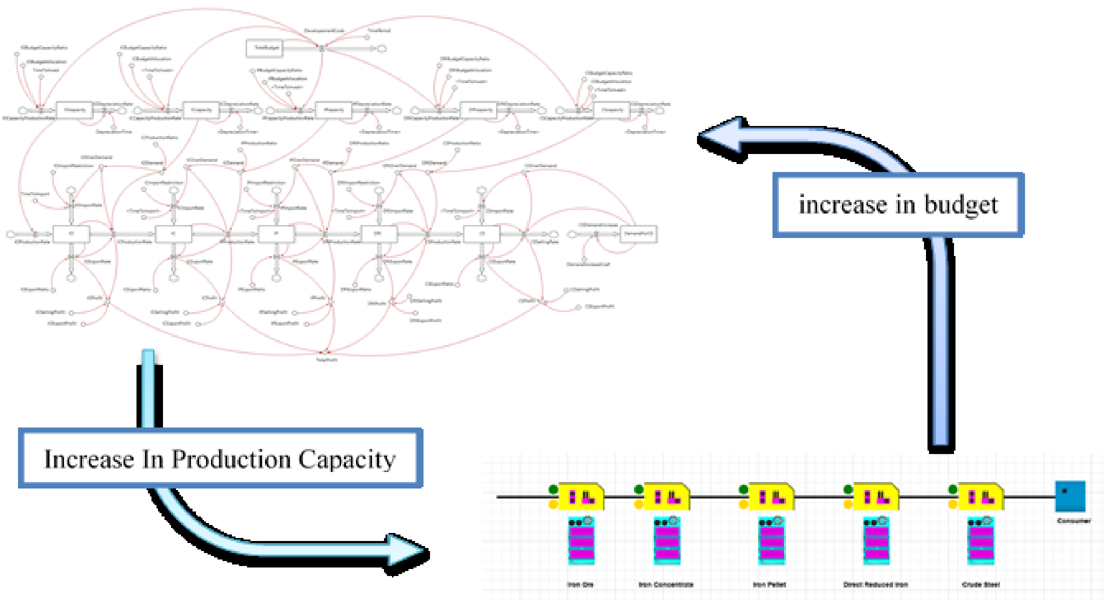


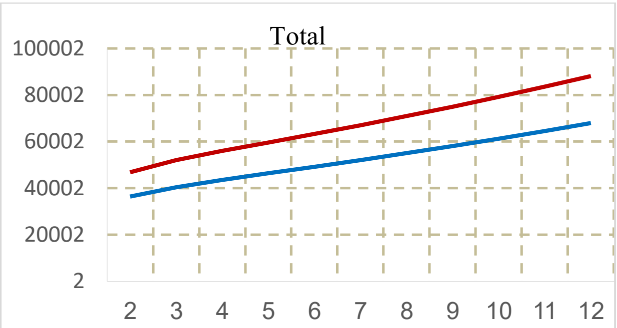
Figure 25. combined model

These intermediate variables increase the dynamic model's budget and the agent-based model's production capacity.The interplay between these two models is as follows: the profitability and cost reductions achieved in the agent-based model over a ten-year period are reflected in the dynamic model at the macro level and in overall policies. The impact of these improvements on overall profitability leads to increased investment and production capacity at the intermediate level.

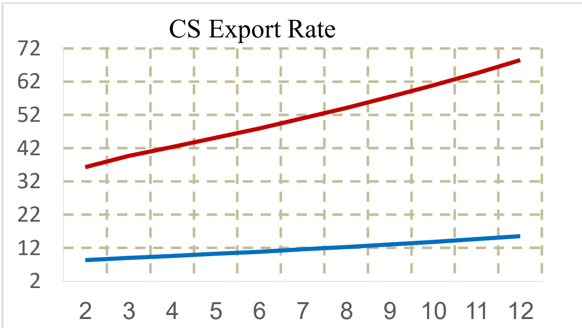
Based on the analysis conducted in both the dynamic and agent-based models, optimal policies must now be considered for the combined model.

Given the policies examined in the dynamic model, increasing the budget for direct reduced iron and crude steel can enhance the overall profitability of the supply chain. The study's analyses also indicate that exporting crude steel is the most profitable segment of Iran's steel supply chain. Therefore, in this section, the costs saved due to reduced distances resulting from Industry 4.0 can be invested in increasing the budget for investing in raw steel production. This investment can lead to increased raw steel production and, considering the constant possibility of exporting raw steel, will not fail.On the other hand, this increase in budget at the macro level leads to increased profitability, and the impact of this profit is reflected in the form of a variable increasing production capacity for raw steel producers.

The results of the dynamic model's profitability after ten years of model execution are shown in Figure 26 (a), and the increase in the export rate of raw steel is shown in Figure 26 (b). These figures demonstrate the successful impact of implementing Industry 4.0 in Iran's steel supply chain and the utilization of its material benefits in investment, increased production, and export of raw steel.



a: overall profitability of the supply chain



b: raw steel export rate over ten years

Figure 26. Impact of Industry 4.0 on the overall profitability of the supply chain and the raw steel export rate over ten years

5. Discussion and conclusion

Based on the system dynamic simulation and the agent-based analysis conducted on the Iranian steel supply chain data, it can be concluded that maintaining a balance between supply and demand at each stage of the supply chain plays a significant role in increasing efficiency and profitability. Increasing production capacity without considering demand, or vice versa, can lead to serious problems in the supply chain.

The model results showed that macro-level policies such as budget allocation, export limits, and support for investments in various parts of the supply chain directly impact the performance of this chain. Therefore, policymakers' decisions should be based on accurate analyses.

Sensitivity analysis, considering the intermediate level of the supply chain and the application of Industry 4.0 to reduce costs, showed that increasing the budget and production capacity in the direct reduced iron and crude steel sectors has a greater impact on the overall profitability of the chain.

It indicates that investment in these sectors can yield higher returns than other sectors. Additionally, increasing the export limit for raw steel, especially compared to other products, can significantly impact the chain's overall profitability. It suggests that exporting crude steel can significantly increase revenue and foreign exchange for the country. Based on the results, several managerial recommendations can be made:

(4) Balanced Investment in Key Sectors: Managers should prioritize budget allocations and investments in the direct reduced iron and crude steel sectors, as these areas yield the highest returns. Allocating resources to these sectors can maximize profitability and ensure a stronger foundation for the entire supply chain.

- Focus on Export Strategies: The results suggest prioritizing crude steel exports over other products can significantly increase revenue. Decision-makers should consider adjusting export policies to capitalize on high-demand markets, potentially enhancing foreign exchange earnings.
- Adoption of Industry 4.0 Technologies: Embracing Industry 4.0, especially in areas such as digitalization, can aid in reducing operational costs and increasing supply chain flexibility.
- Risk Management and Policy Adjustments: Given the sensitivity of the supply chain to macro-level policies like export limits and budget allocations, policymakers need to maintain flexibility. Managers and policymakers should collaborate to develop adaptive policies that adjust to economic shifts and technological advancements.

Based on the analysis of this research, several limitations have been identified, along with recommendations for future research, as outlined below:

(5) Data Availability and Quality: A significant constraint in this study is the limited access to comprehensive data. Future research should aim for extensive datasets to enhance accuracy and detail.

- Generalizability: This study concentrates on Iran's steel supply chain, but the effectiveness of Industry 4.0 strategies can differ across regions and industries. Future research should consider replicating this study in varied national and industrial contexts to improve the generalizability of the findings.
- Long-term Impact Assessment: Due to the evolving nature of technology, it is crucial to assess the long-term impacts of Industry 4.0 on supply chains. Future studies could conduct longitudinal analyses to better understand how these technologies influence supply chain dynamics over time, providing a fuller picture of their impacts.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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Journal of Systems Thinking in Practice
JSTINP, *QUARTERLY*
Homepage: jstinp.um.ac.ir
Online ISSN: 2821-1669, Print ISSN: 2980-9460
Research Article
DOI: 10.22067/JSTINP.2024.89063.1110
JSTINP 2024; Vol. 3, No. 4

Developing a Multi-methodology for Identification and Prioritization of Supply Chain Marketing Strategies for Biotechnology Knowledge-based Companies

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How to cite this article

Deirani, A., Rajabzadeh Ghatari, A., Dehghan Nayeri, M., Nassereddine, M. 2024. Developing a Multi-methodology for Identification and Prioritization of Supply Chain Marketing Strategies for Biotechnology Knowledge-based Companies, *Journal of Systems Thinking in Practice*, *3*(4), pp. 36-62. doi: 10.22067/jstinp.2024.89063.1110.

URL: https://jstinp.um.ac.ir/article_45808.html.

ABSTRACT

While knowledge-based companies can leverage their specialized human and technological resources to increase market share and compete with established firms, they face the challenging and complex task of evaluating and selecting supply chain marketing strategies. This challenge arises due to differences in company type, objectives, size, location, and the varying experiences of decision-makers. The research aims to identify and prioritize supply chain marketing strategies for biotechnology knowledge-based companies by developing and applying a multi-methodological approach. This approach combines the advantages of Soft Operational Research (Soft OR), SWOT analysis, and multi-criteria decision-making (MCDM) to address the complex nature of real-world problems more effectively. The study consists of two main phases. In Phase I, a mixed-method approach using Soft OR (JOURNEY Making method) and SWOT analysis is employed to assess the current situation and formulate potential strategies. A combined AHP-PROMETHEE approach is proposed in Phase II to prioritize the identified strategies. The model enhances decision-making efficiency by helping decision-makers select the best strategy, benefiting from the strengths of Soft OR and MCDM in tackling real-world complexities. Results show that biotechnology knowledge-based companies should prioritize sustainable international presence through proactive, competitive, innovative, and collaborative behaviors, leveraging distinctive resources and strategic alliances to improve technological innovation and knowledge sharing while employing appropriate models to select effective supply chain marketing strategies based on their conditions. Additionally, a sensitivity analysis is conducted to evaluate the impact of criteria weights on the decision-making process, providing valuable insights and confident recommendations for future research.

Keywords

Knowledge-based company, Supply chain marketing strategy, Sustainable competitive advantage, Biotechnology, PROMETHEE, JOURNEY making.

Article history

Received: 2024-07-24
Revised: 2024-09-13
Accepted: 2024-10-16
Published (Online): 2024-12-20

Number of Figures: 5 **Number of Tables: 13** **Number of Pages: 27** **Number of References:43**

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1. Introduction

Knowledge-based companies are undoubtedly the driving force behind the economic systems of both developed and developing countries. The long-term impact of the knowledge-based economy on Iran's economic growth has been well-documented in studies (Behboudi and Amiri, 2010). The primary objective of establishing knowledge-based companies is to effectively commercialize knowledge and transform technological ideas into highly profitable economic products or services (Illiashenko et al., 2023).

Statistics from studies on knowledge-based companies in various countries indicate a high failure rate due to a lack of appropriate development strategies (Cantamessa et al., 2018). However, it is important to note that startups can succeed and thrive with the right strategies and expertise. While less than 10% of startups survive for more than three years, with the figure being approximately 5% in Iran (Khayatian et al., 2019), those that do survive often achieve great success. However, through diligent research, the crucial issue of sustainability can be addressed and ensure the survival of knowledge-based startup companies.

Knowledge-based companies must align their product, market, and supply chain strategies to ensure long-term and sustainable survival in today's complex world. The supply chain comprises organizations involved in the flow of products, services, and information from a source to a customer. To ensure survival and growth, companies must shift their focus from short-term sales and profits to sustainable competitive advantage. By selecting appropriate strategies for supply chain marketing, they can minimize associated risks.

60% of Iran's knowledge-based exports are related to the biotechnology field, and the global market size for this industry is estimated to exceed $800 billion by 2025. Of more than 9,000 Iranian knowledge-based companies, 429 operate in the "Biotechnology, Agriculture, and Food Industries" sector. The two main characteristics of this industry that have led to a relatively low number of companies compared to the total are 1) high complexity and 2) the need for significant capital. These issues seem solvable by looking at the supply chain and taking advantage of its opportunities.

The question arises: How can biotechnology knowledge-based companies select the appropriate supply chain marketing strategy to achieve sustainable competitive advantage? To answer this question, the authors must identify feasible strategies by examining biotechnology knowledge-based companies' environmental and internal conditions. However, to properly develop strategies, it needs to have a thorough knowledge of the key players and influencers in the market. Therefore, the case's complexity arises from two main sources: the inherent complexity of understanding the problem itself, known as structural complexity, and the involvement of multiple participants with diverse objectives, referred to as behavioral complexity. Consequently, researchers often choose to use multiple methods within a single intervention to avoid a narrow perspective and better address the complexities of real-world scenarios (Nassereddine et al., 2021; Sibevei et al., 2022). Thus, an integrated approach is proposed using JOintly Understanding, Reflecting, and NEgotiating strategY (JOURNEY) and SWOT analysis to understand the current situation and formulate possible strategies.

Then, based on how each of these strategies helps the company achieve the ultimate goal of gaining sustainable competitive advantage, we must prioritize them. Since sustainable competitive advantage can have different dimensions, answering this issue requires a multi-criteria decision-making method. Therefore, a merged multi-criteria decision-making (MCDM) approach that combines the analytic hierarchy process (AHP) and preference ranking organization method for enrichment evaluation (PROMETHEE) method is used to rank the alternative solutions.

The first innovation of this research lies in addressing the issue of supply chain marketing strategies specifically for biotechnology knowledge-based companies in Iran. Additionally, the study introduces a novel multi-methodological approach to effectively tackle the problem situation and decision-making. By integrating the strengths of various methods, this new approach improves the efficiency of the decision-making process, assisting decision-makers in selecting the most effective strategy.

The different sections of the paper include the following: In the second section, the research background and theoretical foundations are reviewed. The third section describes the research method, briefly reviewing the JOURNEY making and AHP and PROMETHEE methods. The fourth section presents the research results. The fifth section discusses the results and research limitations. The sixth section provides the conclusion and future recommendations.

2. Background and theoretical foundations of the research

2.1. Biotechnology-based knowledge companies

In recent decades, significant attention has been directed towards biotechnological advancements and the development of knowledge-based companies within this domain. These companies typically secure substantial capital, collaborate with universities and research institutions, and attract elite talent in life sciences to innovate solutions addressing medical, agricultural, environmental, and industrial challenges (Breschi et al., 2014). In other words, biotechnology-based knowledge companies operate within the life sciences sector and

 DOI: 10.22067/JSTINP.2024.89063.1110

collaborate with other enterprises to apply their technologies in other sectors, such as agriculture, food products, energy, and environmental preservation (Nielsen et al., 2022).

Due to inherent risks and specific characteristics, one of the challenges for the success of these companies is sustaining their growth and stability; statistics indicate that most of them either vanish over time or remain small-scale, with only a few transitioning into larger enterprises. Consequently, knowledge-based companies must establish sustainable competitive advantages to continue their growth and development and avoid eliminating from the competitive arena.

2.2. Sustainable competitive advantage

Sustainable competitive advantage refers to a company or organization's ability to continuously maintain its competitive edge in the market. This concept implies that a company should excel in competing against its rivals and maintain its competitive advantage over time and in the face of changing market conditions (Nasifoglu et al., 2020). The literature identifies four primary sources for sustainable competitive advantage: 1) effective supply chain management, 2) innovation and product differentiation, 3) organizational responsiveness, and 4) cost leadership (Vinayan et al., 2012). The study by Khayatian et al. (2016), titled "The Model of Sustainability of Knowledge-Based Companies in Iran," investigates the factors affecting companies' sustainability and the resulting outcomes. It categorizes the influencing factors into internal (founder individual factors, organizational factors) and external (business characteristics, innovation system components). The sustainability outcomes of knowledge-based companies are classified into four categories:

financial results (continuation of sales growth, profitability sustainability),
market results (market share growth, brand credibility),
innovation results (product development,
technology advancement), and entrepreneurship results (job creation, structure formation).

This systematic literature review explores the relationship between dynamic capabilities and competitive advantage in small and medium-sized enterprises. The review introduces three categories of factors: 1) dynamic capabilities, innovation, and brand capabilities; 2) strong interpersonal and inter-organizational relationships with customers, distribution channels, suppliers, and governmental entities; and 3) human capital (Fabrizio et al., 2022). This study examines the relationship between dynamic capabilities, human capital, and supply chain perspectives. It has been noted in several articles that human resources play a crucial role in knowledge-based companies as a source of sustainable competitive advantage. For example, Hatch and Dyer (2004) and Zahra and Nielsen (2002) researched this topic.

In 2019, Shirazi et al. conducted a study on the impact of internal organizational factors on competitive advantage in knowledge-based companies. The factors that were studied included organizational resources such as human, material, and immaterial resources, as well as innovation capabilities such as product and process innovation capability. The study analyzed the impact of these factors on both cost advantage and differentiation advantage. The article explores the impact of technology commercialization performance on the relationship, such as the number of new products, time taken to develop new products, future market, effective use of patents, and technical knowledge. It is suggested that companies based on knowledge may not achieve sustainable success if they cannot commercialize their technologies effectively and lack a long-term strategic market perspective despite having organizational resources, including human resources.

2.3. Supply chain management in biotechnology-based knowledge companies

With increased competition among companies in recent decades and the globalization of markets, it is widely acknowledged that marketing challenges have also intensified. Organizations have realized that improving internal efficiency alone is insufficient for delivering products and services in a timely and cost-effective manner.. Instead, their entire supply chain must become competitive. Hence, it can be observed that supply chain management has become a crucial necessity for maintaining competitiveness in the global market, as noted by Li et al. (2006).

Proper supply chain management leads to opportunities for cost reduction and achieving cost competitive advantage over competitors (Tukamuhabwa et al., 2021). However, cost advantage is not the sole benefit of supply chain management; effective supply chain management can create extraordinary customer value, satisfaction, and loyalty, ultimately improving profitability margins, enhancing profitability, and fostering organizational growth (Flint, 2004). Gathering information from customers and competitors improves the strategy formulation process and is essential for a company's long-term success.

To achieve sustainable competitive advantage, companies must promote a culture of innovation within their organization and plan to share and manage knowledge internally and throughout their value chain (Arsawan et al., 2020; Vickery et al., 2003). Based on network theory and resource-based view, Kang and Na (2020) contend that a network of strategic resources, managed through intricate relationships and communications, which is challenging to replicate, creates a sustainable competitive advantage. Access to strategic resources such as licensing rights to technology or invention in a network centered around a company can lead to the development of the company's value chain and ultimately achieve sustainable competitive advantage (Gassmann and Keupp, 2007).

2.4. Marketing strategy in the supply chain of knowledge-based companies

As mentioned at the beginning of the literature review section, biotechnology-based knowledge companies, due to the nature of their technologies and products, have the potential to be part of supply chains in various industries. It necessitates finding a suitable position for themselves in diverse supply chains. Instead of solely focusing on the end customer and understanding their needs, they must establish relationships with all supply chain members and find a suitable position relative to their competitors within their own chain.

The nature of supply chain strategies is inter-organizational, while marketing strategies are customer-centric. Companies must effectively integrate marketing strategies with their supply chain to achieve success and sustainable competitive advantage. This integration can improve internal strategy formulation processes and enhance strategic alignment with customers and suppliers (Jüttner et al., 2010).

Collaboration within the supply chain is one approach to integrating marketing and supply chain strategies. Four types of collaboration can be defined: intra-organizational, with suppliers, customers, and competitors. These collaborations can lead to developing strategies that meet both parties' needs and preferences. For example, the involvement of customers in the product design process can lead to product improvement, increased customer satisfaction, and ultimately increased sales for the company. As a result, such collaboration can significantly contribute to business sustainability (Chen et al., 2017).

2.5. Marketing strategy alignment

Marketing strategy alignment refers to the development and execution of marketing strategies at the supply chain level by partners involved to create the maximum value for the ultimate supply chain customers (Min and Mentzer, 2000). This alignment leads to improved supply chain performance, which, through enhanced marketing performance, will also result in improved company financial performance (Green et al., 2012).

Knowledge-based companies, mostly small and medium-sized enterprises, must establish strategic collaborations to successfully leverage their intellectual and technological assets, adding value to their supply chain (Stonkute, 2015). Additionally, knowledge brokers can facilitate communication between seekers, providers, innovators, and framers by creating a common language and strengthening bilateral interactions, thus aiding in the technical knowledge marketing of knowledge-based companies (Abbate et al., 2011).

2.6. Research gap

The literature on knowledge-based companies has been examined in detail, with each relevant aspect being addressed separately. Factors influencing sustainable competitive advantage have been studied, as well as the importance of aligning supply chain and marketing strategies. However, it is important to acknowledge that there is potential for further improvement in developing a model for decision-making and prioritization of marketing strategies used by knowledge-based companies within their supply chains. This article aims to fill this gap for biotechnology-based knowledge companies, providing suggestions for necessary changes to improve performance.

Scientific literature highlights multi-methodology as one of the most important developments in OR/MS research (Paucar-Caceres, 2010; Ellakkisa et al., 2024). In conclusion, this paper focused on developing and applying multimethodological intervention benefiting from the advantages of Soft OR and MCDM to deal more effectively with the complex nature of real-world problems. JOURNEY Making has been utilized as a problem-structuring method to comprehend the situation. At the same time, SWOT analysis is employed to develop strategies, and MCDM models are then applied to prioritize these strategies. The proposed model can also be evaluated and applied to other domains in future research.

3. Research methodology

The literature review section highlights the importance of developing marketing strategies in the supply chain and aligning them. In order to address the research question raised in the introduction, a comprehensive approach is required to understand biotechnology-based knowledge companies in Iran, which will enable tailoring marketing strategies to their specific characteristics. A mixed-method (qualitative-quantitative) approach was employed for the research to achieve this understanding.

The study's population comprises emerging and innovative knowledge-based companies in Iran's biotechnology, agriculture, and food industries. The sample was selected by examining the list of biotechnology-based knowledge companies in Tehran on the Vice Presidency for Science and Technology website, from which ten companies were chosen out of the 100 listed. A group of ten experts actively involved in technology commercialization in knowledge-based companies, CEOs of knowledge-based companies, and planners were selected to achieve the research objective. The criteria are obtained through a review of the literature and the use of the Delphi method. The research process is outlined in Figure 1.

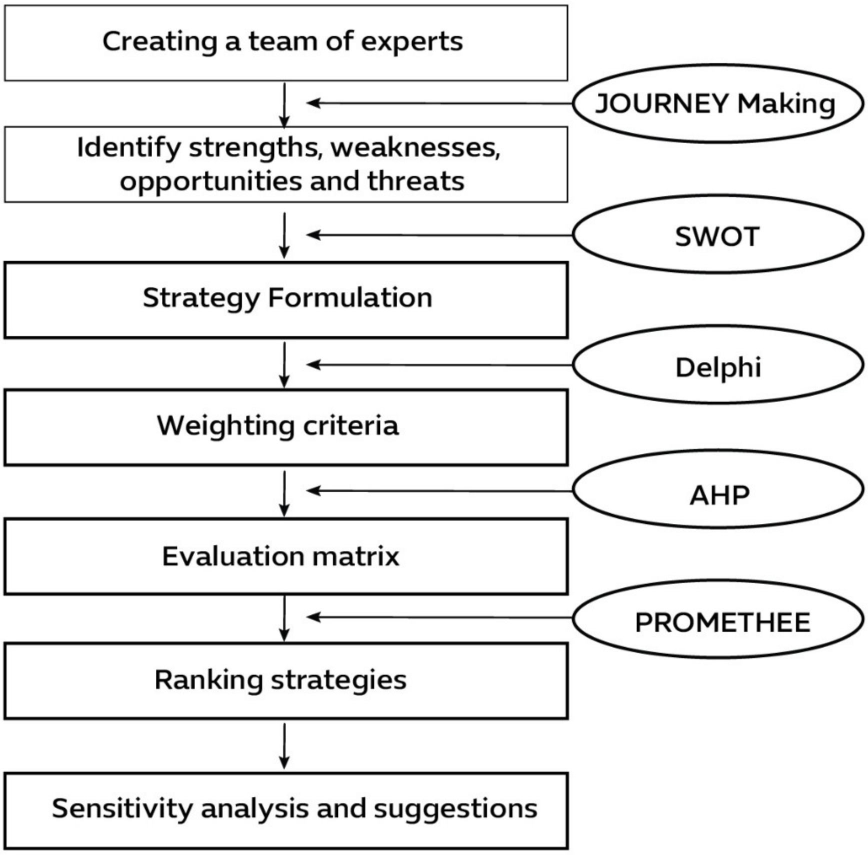

Figure 27. Research process

3.1. JOURNEY making (JM)

JM was originally developed as a methodology to assist organizations in exploring strategic options and solving problems (Eden and Ackerman, 2013). The JM intervention provides a process to help practitioners and scholars understand complex real-world issues. It is based on the premise that every organization has some strategic direction. JM effectively addresses external and internal complexity related to the organizational environment and is associated with methodically developing strategies amidst diverse viewpoints and interests. Essentially, JM involves two main components: (a) identifying emerging strategies and (b) reflecting and negotiating to achieve consensus (refer to Table 1 for more details).

Table 12. JOURNEY making steps

Part	Stage	Step
Surfacing emergent strategies	Familiarization with the situation	Understanding the situation
		Labeling the participant' s roles
	Mapping the situation	Building individual cognitive maps
		Combining maps to form strategy maps
		Analyzing emergent strategies/strategizing
Reflecting and negotiating to gain agreement	Options and scenarios	Generating a set of options
		Generating a set of scenarios
		Comparing the options and scenarios

	Results and reporting	Analyzing the comparison results
		Making recommendations

In the proposed multi-methodology model, the authors focus on the “surfacing emergent strategies” part, especially familiarizing the situation. In the initial stage, the practitioner gains a broad understanding of key issues related to an event and the emergent strategies. Within the JM framework, information is gathered from experts through individual interviews. This information is then applied to the power/interest grid. Compiling a power/interest grid is a remarkable way for JM to analyze stakeholders’ positions and interrelationships. On the grid, according to the stakeholders’ relative power and their interest in the situation, they are classified into four types as follows (Figure 2):

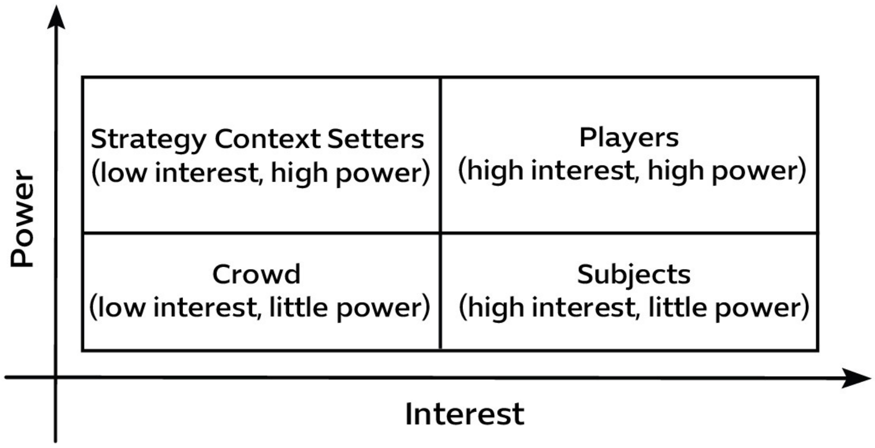

Figure 28. Power/interest grid

3.2. Analytic hierarchy process (AHP)

In the present article, the Analytic Hierarchy Process (AHP), one of the most commonly used methods in multi-criteria decision-making (Saaty, 2004), has been employed to weight the criteria for strategy prioritization. In the AHP method, experts' opinions on the criteria are quantitatively derived through pairwise comparisons.

The AHP method has three main stages:

- Creating a hierarchical structural model
- Pairwise comparison of criteria
- Prioritization of criteria

For pairwise comparisons, the Likert scale is used in various ranges of five, seven, nine, and eleven points. The authors consider a set of criteria $C = (C_j \mid j = 1, 2, \dots, n)$. The results of pairwise comparisons are summarized in the evaluation matrix (A).

$$A = \begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{n1} & \cdots & a_{nn} \end{bmatrix} \quad (1)$$

 DOI: 10.22067/JSTINP.2024.89063.1110

$$a_{11} = a_{22} = \cdots = a_{nn} = 1 \qquad a_{ij} = \frac{1}{a_{ji}} \qquad i = 1,2,\ldots,n \qquad j = 1,2,\ldots,n$$

Then, the normalized evaluation matrix (B) is derived from equation (2), such that for each value in matrix B, the corresponding value in matrix A is divided by the sum of the values in the relevant column:

$$B = [b_{ij}]_{n\times n} \qquad b_{ij} = \frac{a_{ij}}{\sum_{i=1}^{n} a_{ij}} \quad i = 1,2,\ldots,n \qquad j = 1,2,\ldots,n \tag{2}$$

Now, the authors calculate the eigenvector (W), which is composed of the eigenvalues (w_i). The eigenvalues for each row are derived from equation (3) (Kilic et al., 2015):

$$w_i = \frac{\sum_{j=1}^{n} b_{ij}}{n} \; W = \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_n \end{bmatrix} \tag{3}$$

After obtaining the eigenvector (W), the relative priority vector (λ_max) is obtained from equation (4):

$$AW = \lambda_{max} W \; W' = AW = \begin{bmatrix} w'_1 \\ w'_2 \\ \vdots \\ w'_n \end{bmatrix} \; and \;\; \lambda_{max} = \frac{1}{n}\left(\frac{w'_1}{w_1} + \frac{w'_2}{w_2} + \cdots + \frac{w'_n}{w_n}\right) \tag{4}$$

Then, the Consistency Index (CI) and the Consistency Ratio (CR) are calculated using relationships (4). If the Consistency Ratio is less than or equal to 10 percent, there is appropriate consistency among the weights of the criteria. Otherwise, the values of the pairwise comparisons should be reviewed.

$$CI = \frac{\lambda_{max} - n}{n-1} \; CR = \frac{CI}{RI} \tag{5}$$

The Random Consistency Index (RI) for different n values can be calculated from the table 2.

Table 13. Random consistency index (RI)

n	1	2	3	4	5	6	7	8	9	10
RI	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49

In this paper, due to the application of the Group Analytic Hierarchy Process (AHP) for criteria weighting, experts are requested to perform prioritization individually. Eventually, to amalgamate their opinions and arrive at a final eigenvalue, the geometric mean is taken between their values for each criterion (Saaty, 2004).

3.3. PROMETHEE method

The PROMETHEE method is a multi-criteria decision-making approach that supports various studies' decision-making processes. This method, belonging to the family of outranking comparison methods, compares options based on degrees of preference and indifference toward each other. In this research, PROMETHEE is employed to prioritize strategies. Among the benefits of using this method for strategy prioritization are the ability to weigh different criteria, select various preference functions for different criteria depending on their type and options, and the sensitivity analysis of the prioritization outcome based on changes in criteria weights and preference functions.

The steps of the PROMETHEE method are as follows (Behzadian et al., 2010):

1- Determining the pairwise differences between options based on each criterion:

$$d_j(a,b) = g_j(a) - g_j(b) \tag{6}$$

In equation (1), $d_j(a,b)$ represents the difference between options a and b in criterion j.

2- Calculating the preference function for each criterion:

$$P_j(a,b) = F_j\left[d_j(a,b)\right] \qquad j = 1, \dots, n \tag{7}$$

In equation (2), the function $P_j(a,b)$, or the preference function, indicates the preference of option a over b based on the magnitude of their difference in criterion j.

3- Calculating the overall preference index:

$$\forall\, a, b \in A \quad \pi(a,b) = \sum_{j=1}^{k} P_j(a,b) w_j \qquad j = 1, \dots, n \tag{8}$$

Where set A consists of the options available for decision-making.

The preference index of a over b, $\pi(a,b)$, is derived from the weighted sum of preferences of a over b in each criterion, where w_j is the weight of each criterion.

Calculating the outranking flows, partial ranking in PROMETHEE I:

$$\phi^+(a) = \frac{1}{n-1} \sum_{x \in A} \pi(a,x) \tag{9}$$

$$\phi^-(a) = \frac{1}{n-1} \sum_{x \in A} \pi(x,a) \tag{10}$$

$\phi^+(a)$ is the positive outranking flow and $\phi^+(a)$ is the negative outranking flow for each option a.

- Calculating the net outranking flow, complete ranking in PROMETHEE II:

$$\phi(a) = \phi^{+}(a) - \phi^{-}(a) \tag{11}$$

In equation (11), $\phi(a)$ is the net outranking flow for each option.

A critical aspect of the PROMETHEE method is selecting an appropriate preference function for each criterion (Nassereddine and Eskandari, 2017). Changing the type of preference function alters the outcome of the decision-making problem. Therefore, careful consideration must be given to the type of criterion and the objective of the decision-making issue when selecting it.

Six types of preference functions for criteria in the PROMETHEE method are as follows, which are observable in Figure 3 (Brans and Vincke, 1985):

(6) Usual Criterion: In this case, if the scores of two options are equal in one criterion, there will be no difference, and if one is slightly higher, it will be chosen.
(7) U-shaped Criterion: As long as the difference in scores between two options is less than q, there will be no difference.
(8) V-shaped Criterion: As long as the score difference between two options is less than p, the preference is weak, and the value of the preference function equals the ratio of the score difference to the threshold value (p). With an increase in d and passing the threshold p, the preference is strict, and the value of the function will be one.
(9) Level Criterion: Similar to the U-shaped criterion, but preferences increase stepwise. The preference function has three states: indifference, weak preference, and strict preference.
(10) Linear Criterion: It has two values q and p, which are the thresholds for indifference and preference, respectively. Similar to the V-shaped criterion, for differences in scores greater than q, the value of the preference function equals the ratio of (d-q) to (p-q).
(11) Gaussian criterion: The preference function value for positive score differences follows a Gaussian function.

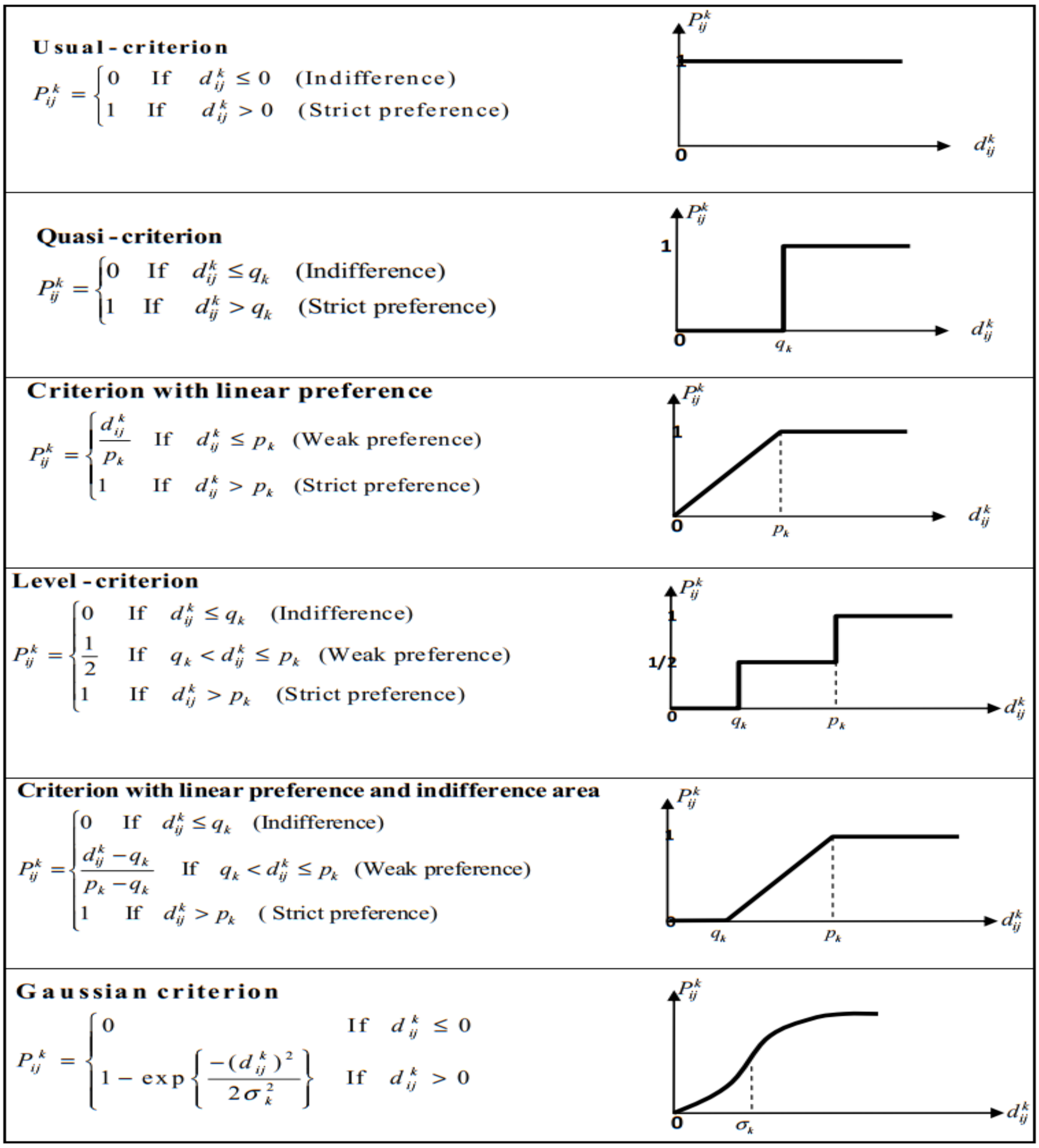

Figure 29. Preferred functions of the PROMETHEE method

A general schematic of the supply chain process in these companies was drawn based on interviews with experts from companies active in the biotechnology, agriculture, and food industries. In these companies, skilled and experienced human resources, advanced laboratory equipment, and high-quality raw materials are key success factors. Typically, nascent knowledge-based companies in this sector lack production equipment, distribution networks, and sales channels, thereby losing the opportunity for sustainable and long-term commercialization of products. Figure 4 shows the supply chain in the biotechnology industry.

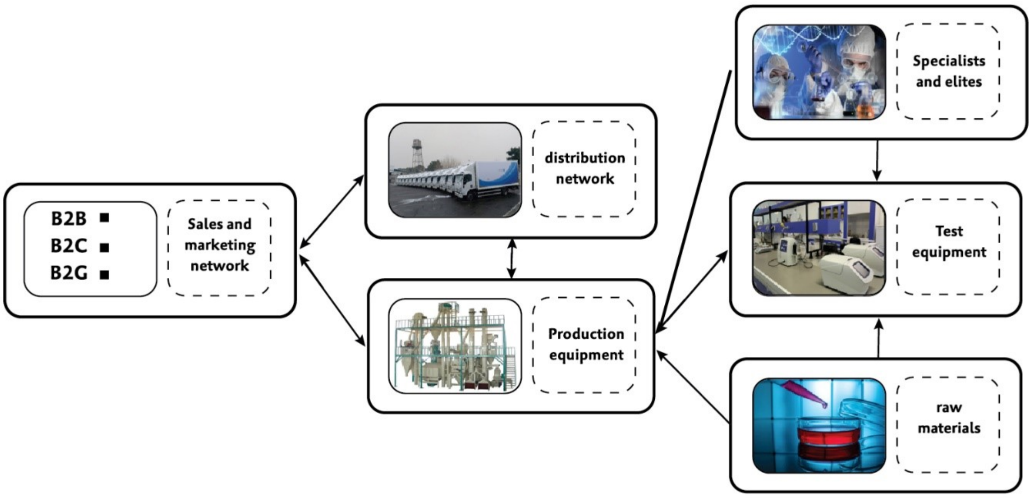

Figure 30. Supply chain in the biotechnology industry

This section contains JM's results and responses to the research questions based on information obtained from expert interviews.

JM can be an effective research tool for overcoming the complexity of problems and aiding decision-making in practice. It is useful for understanding situations, developing options, and predicting scenarios. Therefore, the first stage of JM has been applied to familiarize with the situation. This stage (familiarization with the situation) involves understanding the situation and labeling the participants' roles. The results of the participants' roles are listed in Table 3.

Table 14. Power and Interest of participant

Nb	Actor's name	Labelling the participant' s role 1 TO 5	
		Power	**Interest**
1	Suppliers	٤.1	3
2	Knowledge Based Companies	3.1	4.5
3	Customers	3.2	2.8
4	Brokers	3.3	2.3
5	Knowledge-based deputy	3.4	٤.4
6	Universities	2.6	3.8
7	Foreign start-up companies	4.7	2.9
8	Export management companies	3.3	4.3
9	Science and technology parks	4.6	4.5

Following the JM phase, experts now possess a more comprehensive understanding of the issue, particularly regarding the key players, enabling them to respond to questions more effectively and achieve more dependable results. Following the JM phase, experts now possess a more comprehensive understanding of the issue, particularly regarding the key players, enabling them to respond to questions more effectively and achieve more dependable results. The questions are:

Question 1: What are the environmental threats and opportunities for marketing by biotechnology knowledge-based companies in the supply chain?

The experts were asked to outline the supply chain process around their company and identify strengths and weaknesses for marketing in the chain. The interviews were conducted and coded, as shown in Table 4. After summarizing the items, the experts were requested to assign a numerical value ranging from 1 to 4 to each of them based on their significance as either a strength or weakness (1: indicating a severe weakness, 2: indicating a relative weakness, 3: indicating a relative strength, and 4: indicating a strong strength). The relative importance coefficient was also determined for each item, starting from number one. The final score for each item was calculated by multiplying the rank value by the relative importance coefficient.

Table 15. Internal factors assessment matrix

	No	Internal factors	Weigh	Rating	Weighted Score
Strengths	S_1	Benefiting from an expert workforce and access to elite networks in biotechnology, agriculture, and food industry parks.	0.04	4	0.16
	S_2	The cost of domestic knowledge-based products is lower than that of their foreign counterparts.	0.06	4	0.24
	S_3	The possibility of exporting many products related to the food industry as raw materials (B2B) and finished products (B2C).	0.08	4	0.32
	S_4	The dynamism and agility of the organizational structure and bureaucracy are greater than those of established companies.	0.04	3	0.12
	S_5	Expanding the atmosphere of entrepreneurship and business development among university graduates.	0.03	3	0.09
	S_6	Possession of medium and advanced technologies in the field of biotechnology by knowledge-based companies.	0.07	3	0.21
	S_7	Possession of patents by some of the founders.	0.05	3	0.15
	S_8	The ability to use technologies related to biotechnology, agriculture, and food industries in each other's industries and the possibility of their joint development.	0.09	4	0.36
Weaknesses	W_1	Weakness in offering new products and lack of market confidence in new knowledge-based products compared to established companies.	0.05	1	0.05
	W_2	The unwillingness of new knowledge-based companies to expand and their tendency to settle for a small number of products with average profit.	0.04	2	0.08
	W_3	Weakness in knowledge management in the supply chain of knowledge-based companies.	0.03	1	0.03
	W_4	Lack of attention to the importance of managing the supply chain of products and technologies in most knowledge-based companies.	0.08	1	0.08
	W_5	The low motivation of specialists in knowledge-based companies is due to relatively low salaries and benefits.	0.06	2	0.12
	W_6	Weakness in management and system knowledge, especially regarding scale-up.	0.05	2	0.1
	W_7	Weakness in inter-company cooperation and the establishment of joint research and development centers.	0.04	2	0.08
	W_8	Higher domestic product prices compared to market expectations.	0.07	2	0.14
	W_9	There is a lack of loyalty among specialized forces and difficulty in long-term planning for the company.	0.04	2	0.08
	W_{10}	Lack of communication and weakness in attracting technology investors to commercialize patents.	0.08	2	0.16
		Sum	$\sum=1$		2.57

The internal factors assessment matrix indicates that biotechnology knowledge-based companies have more strengths than weaknesses, with a score of 2.57 in the last row. However, the difference in numerical values is insignificant, suggesting that strengths and weaknesses are relatively balanced.

Question 2: What potential environmental factors may biotechnology knowledge-based companies encounter in the marketing supply chain?

Similar to strengths and weaknesses, opportunities and threats were identified by experts. The list of opportunities was then elaborated by studying other upstream documents in the biotechnology development field. The experts were presented with the list again to determine the relative importance coefficient and rank of each opportunity and threat through hierarchical analysis (Table 5).

Table 16. External factors assessment matrix

	No	External factors	Weigh	Rating	Weighted Score
Opportunities	O_1	The opportunity to benefit from the empowerment and commercialization services of knowledge-based companies provided by the Vice President for the Development of Knowledge-Based Companies.	0.02	3	0.06
	O_2	Supporting programs of the technology corridor to the market through the Deputy for the Development of Domestic and Foreign Markets of Knowledge-Based Companies.	0.03	3	0.09
	O_3	The increase in the exchange rate pushes the market towards domestic knowledge-based products, leading to a preference for these products over imported ones.	0.09	4	0.36
	O_4	The opportunity to benefit from Iran's National Fan Market Network, a new technology exchange infrastructure that serves as a platform to present technological capabilities and needs.	0.05	3	0.15
	O_5	The import of certain biotech raw materials, such as cultivation medium, has been stopped due to sanctions.	0.06	3	0.18
	O_6	The import of certain biotech raw materials, such as cultivation medium, has been stopped due to sanctions.	0.03	3	0.09
	O_7	The high priority of biological technologies, agriculture, and food industries is to meet the country's essential needs in health, environment, and food security.	0.04	3	0.12
	O_8	Iran's membership in the International Centre for Genetic Engineering and Biotechnology (ICGEB) and the implementation of joint biotechnology research with some advanced countries in agriculture.	0.05	4	0.2
	O_9	Executive regulations to facilitate investment and export development for knowledge-based companies and institutions.	0.02	3	0.06
Threats	O_{10}	Knowledge-Based Production Leap Law.	0.04	3	0.12
	O_{11}	Larg Iranian manufacturing companies with a history of exports, market presence, and production equipment exist.	0.05	3	0.15
	T_1	The import of contraband goods is similar to some domestic knowledge-based products.	0.09	1	0.09
	T_2	The existence of intermediaries who sell knowledge-based products reduces the profit margin for producers.	0.06	2	0.12
	T_3	Weaknesses in administrative structures and procedures related to the establishment and development of knowledge-based companies.	0.03	2	0.06

No	External factors	Weigh	Rating	Weighted Score
T_4	The high inflation rate in Iran has led to economic instability, resulting in a reluctance among people to start knowledge-based companies, especially manufacturing ones.	0.05	1	0.05
T_5	The high emigration rate among the country's elites decreased interest in value-creating activities.	0.04	1	0.04
T_6	Weaknesses in the infrastructure related to the smart supply chain and its strategic management.	0.06	2	0.12
T_7	The incompleteness of intellectual property and copyright laws in Iran.	0.03	2	0.06
T_8	The immaturity of the intellectual property market in Iran.	0.03	2	0.06
T_9	Many raw materials are imported, such as those needed to make acidifiers, which are animal feed preservatives.	0.06	1	0.06
T_{10}	The low quality of imported raw materials despite their high cost.	0.04	2	0.08
	Sum	$\sum=1$		2.38

As observed in the last row of the external factors assessment matrix, the score is 2.38, below 2.5. It suggests that environmental threats are more significant than opportunities and should be considered when developing a strategy.

Question 3: Regarding the SWOT analysis, what marketing strategies could be implemented by biotechnology knowledge-based companies in the supply chain?

After identifying the strengths, weaknesses, opportunities, and threats, the next step is to formulate strategies. Strategies are derived from the intersection of environmental conditions and organizational status and fall into four general categories: aggressive (SO), conservative (WO), competitive (ST), and defensive (WT). The SWOT matrix in Table 6 suggests six marketing strategies for nascent and innovative knowledge-based companies in the supply chain. The six strategies were selected based on the final scores of each opportunity, threat, strength, and weakness.

Table 17. SWOT matrix

	Strengths	Weaknesses
Opportunities	SO strategy 1) Using production equipment available in growth centers and science and technology parks and selling through large companies'brand and distribution network. O_6 ،O_{11} ،S_6 ،S_7 5) Conducting joint research and development with companies active in other industries (technology spillover). O_4 ،O_7،S_1 ،S_8	WO strategy 4) Signing a cooperation agreement with export management companies with a distribution and sales network can help develop the knowledge-based brand. T_2 ، T_6 ،T_{11} ،S_3 ،S_2 ،S_4
Threats	ST strategy 2) Production and joint investment with knowledge-based companies active in their supply chain: O_4 ،O_9 ،O_{10} ،W_1 ،W_6 ،W_7 3) Conclusion of technology transfer + product export contracts with neighboring start-up companies: O_2 ،O_8 ،O_6 ،W_4 ،W_3 ،W_8	SW strategy 6) Definition of academic research and development projects and then their commercialization. T_5 ،T_7 ،T_8 ،W_{10} ،W_9 ، W_7

Question 4: What are the prioritization criteria for determining the best marketing strategy in the supply chain for biotechnology knowledge-based companies (components of sustainable competitive advantage)?

The criteria were collected by reviewing relevant literature on supply chains in small and medium-sized knowledge-based companies. The collected criteria relate to supply chain performance, marketing performance, and sustainable competitive advantage (Table 7).

Table 18. Criteria for strategies

Nb	Criteria	Code	Definition	Ref.
1	Strategic relationship with suppliers	C_1	A long-term relationship between the organization and its suppliers is aimed at leveraging the strategic and operational capabilities of the participating organizations to achieve continuous benefits.	(Li et al., 2006)
2	communication with clients	C_2	A set of actions taken to manage customer complaints, establish long-term relationships with customers, and improve customer satisfaction.	(Li et al., 2006)
3	Information sharing level	C_3	The extent to which critical and proprietary information is communicated to a supply chain partner.	(Li et al., 2006)
4	Level of information quality	C_4	Accuracy, timeliness, and adequacy of information exchanged.	(Li et al., 2006)
5	Access to strategic resources	C_5	Resources that are valuable, rare, inimitable, and non-substitutable are called strategic resources, such as advanced technologies.	(Nasifoglu et al., 2020)
6	Innovation	C_6	Innovation has various dimensions, including product, process, and organization. Innovation contributes to competitive advantage by replacing old products with new ones and maintaining market share.	(Tidd et al., 2006)
7	operational excellence	C_7	It refers to an organization providing higher value to its customers while operating faster, better, and more cost-effectively.	(Bag et al., 2020)
8	Access to knowledge and technology brokers	C_8	Knowledge brokers facilitate communication between knowledge seekers, providers, innovators, and framers.	(Magliocca et al., 2023)
۹	Access to new markets	C_9	Markets in other cities and countries, as well as related industries.	(Javalgi et al., 2011)
10	Access to basic infrastructure	C_{10}	Technological infrastructure that facilitates various supply chain activities, such as equipment for transporting and storing food under special conditions.	(Chakraborty et al., 2023)
11	Facilitating social entrepreneurship	C_{11}	The possibility of engaging in activities that seek to create social value, not just generate income and economic value.	(Nayak et al., 2022)

The literature was initially reviewed to identify the essential criteria for selecting supply chains in small and medium-sized knowledge-based companies. Through this review, eleven criteria were identified. Additionally, two rounds of the Delphi method were conducted to reach a consensus among experts, with no significant differences observed in their opinions after the second round. Based on the experts' opinions, six of the most important criteria were selected: strategic relationship with suppliers (C1), customer relationship (C2), access to strategic resources (C5), innovation (C6), access to technology brokers (C8), and access to new markets (C9).

Question 5: What are the relative weights of the criteria?

The table shows the weights of the criteria and other values related to the AHP method by presenting the six criteria listed in the previous section (question 5) to the experts and asking them to make pairwise comparisons between these criteria (Table 8).

Table 19. Pairwise comparison results of criteria

Criteria	Symbol	Criteria in software	Weight	Indexes
Strategic relationship with suppliers	C_1	Suppliers	0.16	
communication with customers	C_2	Customers	0.09	λ_{max}= 6.31
Access to strategic resources	C_5	Resources	0.28	CI= 0.063
Innovation	C_6	Innovation	0.03	RI= 1.24
Access to knowledge and technology brokers	C_8	Brokers	0.05	CR= 0.05
Access to new markets	C_9	New Markets	0.39	

As mentioned above, a consistency ratio of less than or equal to 10% is acceptable, which is 5% here. According to the experts, accessing new markets is the most important criterion, with a weight of 39%, followed by accessing strategic resources with 28%, strategic relationships with suppliers with 16%, customer relationships with 9%, access to technology brokers with 5% and finally innovation with 3%. It seems that when formulating marketing strategies in the supply chain, companies are looking for opportunities to enter new markets, and accordingly, this criterion has the highest score. The other two important criteria, strategic resources and strategic relationships with vendors rank second and third, respectively, reflecting the importance of raw materials, equipment, and other resources, including knowledge and technology, in the biotechnology value chain. As most biotechnology companies are at the beginning of the value chain, the relationship with the final customers of the chain is less important for them. Technology intermediaries and innovation also received the lowest scores. This may be due to the poor functioning of intermediaries in the past, their insufficient knowledge of the market, or the fact that innovation can be seen as an inherent characteristic of all knowledge-based firms.

Question 6: Based on the weightings obtained for the criteria, which strategies have the greatest impact on achieving sustainable competitive advantage?

The Visual PROMETHEE software can be used to prioritize strategies based on the weighted criteria in question 5 and the methods developed in response to question 3. Figure 5 shows the decision model used to answer this question.

 DOI: 10.22067/JSTINP.2024.89063.1110

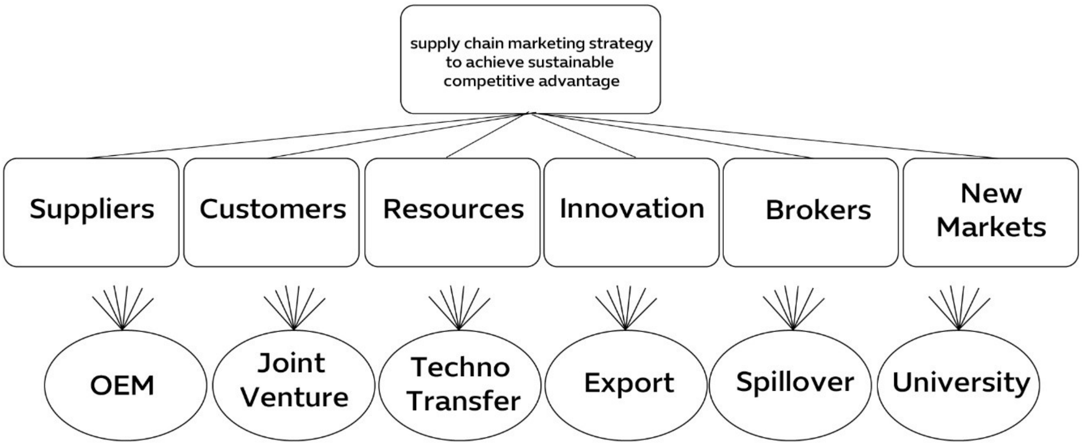

Figure 31. Decision model for prioritizing strategies

The six strategies resulting from the SWOT method are:

OEM production of products by knowledge-intensive companies under brands of domestic and foreign pharmaceutical and food companies (OEM).

(12) Joint production and investment with knowledge-intensive companies in their supply chain (joint venture)

- Export contracts + technology transfer to foreign start-up companies (Technology Transfer)
- Collaboration with export management companies in the pharmaceutical and food industry, such as "Avita Bios Pharma" (Export)
- Collaborative R & D to develop products in the supply chain of different industries based on technologies available in the knowledge-based company (technology spill-over).
- Definition of university R&D projects and their subsequent commercialization (University)

New titles used in the Visual PROMETHEE software for each option (strategy) are given in brackets. Using the Delphi method to create a matrix for evaluating the options, the experts were asked to rate each strategy on a scale from 1 to 9 according to how much it strengthens a criterion. The scoring method is shown in Table 9.

Table 20. Nine-point intensity of importance scale and its description.

Definition	**Intensity of importance**
Equally important	1
Moderately more important	3
Strongly more important	5
Very strongly more important	7
Extremely more important	9
Intermediate values	2, 4, 6, 8

Then, by averaging the expert scores to each strategy for each criterion, the strategy evaluation matrix (options) is obtained in Table 10.

Table 21. Strategy evaluation matrix

Criteria and alternatives	New Markets	Brokers	Innovation	Resources	Customers	Suppliers
Weight	0.39	0.05	0.03	0.28	0.09	0.16
OEM	7.2	5.4	6.4	4.8	6.8	5.4
Joint Venture	4.6	3.8	6.2	3.2	5.2	6.2
Techno Transfer	6.8	6.6	5.8	3.2	5.8	4.8
Export	8.8	6.6	3.8	5.2	7.6	4.6
Spillover	6.8	6.8	7.2	6.6	5.6	6.2
University	3.6	4.4	7.4	5.8	2.6	5.8

Due to the nature of the decision criteria, which are all qualitative and quantified using the Likert spectrum, the linear ranking function of the Visual PROMETHEE software was used for them. Table 11 shows the results of the prioritization strategies.

Table 22. Strategy prioritization

Strategies	Positive flow ($\emptyset^{+}$)	Negative flow ($\emptyset^{-}$)	Net flow ($\emptyset$)	Rank
OEM	0.2001	0.0616	0.1385	3
Joint Venture	0.0916	0.3796	—0.2880	6
Techno Transfer	0.1273	0.2757	—0.1484	4
Export	0.3247	0.1423	0.1823	2
Spillover	0.3589	0.0257	0.3331	1
University	0.1598	0.3774	—0.2176	5

Strategies can be used together and create synergies. Combining strategies can lead to greater or lesser synergies or even contradictions that threaten overall strategic performance. For this reason, the experts were asked to compare pairs of strategies in terms of synergies using the nine-point Likert scale, and the average results for synergies between strategies are presented in Table 12. A comparison of the prioritization table results from the two methods, PROMETHEE and Synergy. For a more reliable result, it is better to take weighted averages between the results (Nassereddine et al., 2019). It means that each decision system should be taken into account according to its importance, with a weight of 1 in total, and finally, the ranking of the strategies will be obtained.

Table 23. Pairwise comparison of synergy between strategies

Strategies	OEM	Joint Venture	Techno Transfer	Export	Spillover	University	Total synergy score
OEM	-	6.2	6	6.8	4.2	2.6	5.16
Joint Venture	-	-	6	3.6	6.2	4.4	5.28
Techno Transfer	-	-	-	8.2	5	4.6	5.96
Export	-	-	-	-	4.6	2.4	5.12
Spillover	-	-	-	-	-	4.2	4.84
University	-	-	-	-	-	-	3.64

The results of MCDM and synergy evaluation are presented in Table 13. Table 13 gives us a systemic view of evaluation by presenting the rank of each strategy (MCDM results) and the share of each from the collective strategies (synergy results). The final rank can be calculated as shown in the equation below.

Table 24. MCDM and synergy results

Criteria	MCDM	Rank	Synergy	Rank
OEM	0.1385	3	5.16	3
Joint Venture	—0.2880	6	5.28	2
Techno Transfer	—0.1484	4	5.96	1
Export	0.1823	2	5.12	4
Spillover	0.3331	1	4.84	5
University	—0.2176	5	3.64	6

$$Final\ Rank = W_1 * PROMETHEE\ Ranking + W_2 * Synergy\ Ranking$$

$$W_1 + W_2 = 1 \tag{12}$$

W1 is the relative importance of using only one strategy, while W2 is the relative importance of synergy result. the allocation of weights is based on expert opinion.

4. Discussion and research limitations

Biotechnology is widely used and growing in the pharmaceutical, agricultural, and food industries. Developed countries are increasingly using biotechnology to improve the quantity and quality of agricultural and food products to maintain their food security, especially in the face of droughts and population growth (Björnberg et al., 2015). Additionally, biotechnology has numerous applications in the medical and disease treatment fields. Iran is a leading country in Western Asia for human drug production infrastructure. It is currently one of the top 10 countries in the world and the first in the region for biotechnology drug production. The country produces 28 types of biotechnology drugs.

As mentioned in the results section, according to the PROMETHEE model, the first strategy is the spillover strategy or technology spillover. In order to use their technologies in different industries and to better define their development path, biotechnology, agri-food, and knowledge-based companies need to carry out joint research and development projects. For example, a company producing human probiotics can expand its supply chain if it can develop animal probiotics for livestock and poultry to be used in the agri-food industry. An ornamental plant tissue culture company will have new value chain development opportunities through the cultivation of medicinal plants. The use of the technology exchange infrastructure (technology marketplace) available to companies through the Office of the Deputy President for Science and Technology can also be effective.

Cooperation with export management companies is the next strategy in the chosen model (export). Companies that provide sales channels specifically for biotechnology companies (e.g., AvitaBiosPharma) can take advantage of key success factors, contribute to the rapid growth of knowledge-driven companies, and secure their success in competition with large and established companies. In some cases, depending on their resources, knowledge-based companies may prefer to pursue an OEM strategy rather than a branding strategy and direct customer relationships. For example, a probiotics company may initially choose to sell its product wholesale to a domestic or export-oriented foreign food manufacturer and expand sales to other direct marketing strategies in the future.

The Deputy of Development of Knowledge-Based Enterprises provides infrastructure for biotechnology companies to conclude technology transfer and export agreements with emerging foreign companies in countries like China, Russia, Lebanon, Turkey, and Iraq. Technology transfer involves a company transferring a specific biotechnology technology to another company in exchange for an export license to that country. Future research may focus on the method of technology transfer.

As places for conducting applied research, universities can assist nascent knowledge-based companies that lack resources for hiring specialized personnel at the beginning of their journey. Defining university research and development projects and supporting them can lead to forming relationships between knowledge-based companies and one of their key success factors, namely university experts, expanding the company's human network in the future.

The study's model ranked the Joint Venture strategy as the least effective. It may be because emerging knowledge-based firms often lack production equipment and rely solely on laboratory equipment in growth centers and science and technology parks. Therefore, this strategy could facilitate the future exchange of technology and production infrastructure between knowledge-based firms. However, it first needs to be integrated with other strategies.

It is important to note that the strategies that can be adopted and their prioritization may differ depending on the industry in which the knowledge-based company operates, its lifespan and size, and the weight of criteria. For this study, we selected companies in the biotechnology, agriculture, and food industries from the list of knowledge-based companies available on the website of the Deputy of Knowledge-based Companies Development of the Presidency. We aimed to include only nascent and innovative companies to ensure reliable research results. However, there were still differences in terms of the lifespan and size of the companies.

5. Conclusion and future recommendations

Evaluating and selecting the appropriate supply chain marketing strategy is an important yet challenging task for knowledge-based companies due to differences in company type, objectives, size, location, the varying and inconsistent experiences of decision-makers, and the interaction among several actors. This paper focused on developing and applying multimethodological intervention benefiting from the advantages of Soft OR and MCDM to deal more effectively with the complex nature of real-world problems. JOURNEY Making has been utilized as a problem-structuring method to comprehend the situation. At the same time, SWOT analysis is employed to develop strategies, and MCDM models are then applied to prioritize these strategies. As a summary of the research findings, the attention of managers of biotechnology knowledge-based companies shown that the goal of companies should be a sustainable international presence through opportunity seeking and finding a superior competitive position based on distinctive resources and creating value-creating networks, and companies are expected to exhibit proactive, competitive, innovative, collaborative, and customer-centric behaviors. Also, technology-oriented companies should be proactive in strategic alliances that will have effects such as improving technological innovations and knowledge sharing in inter-organizational collaborations. Furthermore, companies should define and use appropriate criteria and models for selecting suitable marketing strategies in the supply chain based on their specific conditions.

It is suggested that the prioritization model of strategies for knowledge-based companies in other sectors be redesigned and compared between companies in different sectors. For example, it can be examined how a model derived for information technology knowledge-based companies differs from a model derived for biotechnology knowledge-based companies in terms of similarities and differences. The model can be enriched by increasing the number of criteria and formulating strategies. Additionally, increasing the number of samples can improve the accuracy of the decision model and prioritization. Future research could explore formulating implementation plans for each strategy.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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Journal of Systems Thinking in Practice
JSTINP, *QUARTERLY*
Homepage: jstinp.um.ac.ir
Online ISSN: 2821-1669, Print ISSN: 2980-9460
Research Article
DOI: 10.22067/JSTINP.2024.88156.1105
JSTINP 2024; Vol. 3, No. 4

Dynamic Modeling of Controllable Returns in E-commerce: The Impact of Seller Restrictions on Platforms

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How to cite this article

Khadivar, A., Norouzi, M., Hadi Najafabadi, M., 2024. Dynamic Modeling of Controllable Returns in E-commerce: The Impact of Seller Restrictions on Platforms. *Journal of Systems Thinking in Practice*, *3*(4), pp.63 -81. doi:10.22067/jstinp.2024.88156.1105.

URL: https://jstinp.um.ac.ir/article_45902.html.

ABSTRACT

Effective operations management is pivotal in driving revenue and profitability for organizations in today's business world, particularly in e-commerce and online markets. Among the critical areas of operations management, product returns have garnered increasing attention. Although product returns could benefit businesses by increasing customer loyalty, trust, and satisfaction, reducing advertising costs, and attracting new customers for sellers, they can also harm sellers by increasing transportation costs, reducing profits, and affecting product quality. As a result, e-commerce platforms need to determine an optimal level of strictness in product returns policy. This study examines the dynamic model of seller-controllable returns in e-commerce platforms and investigates how imposing restrictions on sellers with high return rates influences overall return volume. The findings demonstrate that as seller restrictions tighten, the return rate decreases, suggesting that e-commerce platforms should consider implementing policies restricting sellers with high return rates to reduce their product returns.

Keywords

Product returns, Return policies, E-Commerce Platforms, System dynamics.

Article history

Received: 2024-05-20
Revised: 2024-10-29
Accepted: 2024-11-09
Published (Online): 2024-12-20

Number of Figures: 12 **Number of Tables: 2** **Number of Pages: 19** **Number of References:28**

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1. Introduction

The online shopping industry has become a vital part of the business world today, as more and more people prefer to buy things online (Gupta et al., 2023). To compete in this market, online sellers must offer good customer service and improve customer satisfaction. One way to do this is to allow customers to return the products they buy if unsatisfied (Abdulla et al., 2022). However, this poses a major challenge for online platforms, as product returns have advantages and disadvantages. On the one hand, product returns may increase customer trust and loyalty, lower advertising costs, and attract new customers for sellers. On the other hand, product returns can also increase transportation costs, lower profits, and damage the quality of products. Therefore, online platforms must find the best balance between being strict or permissive in their product returns management (Stock et al., 2006).

Customers could have different reasons for returning products, affecting customer satisfaction, seller profit, and platform performance. Stock et al. (2006) classified product returns into two main types: (1) Uncontrollable returns when the customer changes his or her mind and returns the product in the same condition as he or she received it. This type of return is not the seller's fault and does not lower the seller's performance rating. In this case, the product can be sold again. However, the business unit has little control over this type of return in the short term. (2) Controllable returns: when the customer returns the product because of something the seller did wrong, such as sending the wrong product, delivering a defective or broken product, or delivering late. This type of return is the seller's responsibility and lowers the seller's performance rating. In this case, the product cannot be sold again or can only be sold at a lower price. On the other hand, the business unit can reduce this type of return by implementing policies.

This research aims to develop a dynamic model for e-commerce platforms and examines how they can reduce controllable returns, which are not related to customer preferences. The authors investigate how restriction policies, which restrict sellers with high return rates from the platform, influence the total number of controllable returns and customer satisfaction. To do this, the authors build the theoretical framework, specify the system's assumptions, parameters, and dynamic equations, and run the model using the Vensim PLE simulator. Finally, the authors compare the model results with real data from a leading e-commerce platform in Iran, perform sensitivity analysis, assess different scenarios, and report and present the results and recommendations.

The scientific contribution of this research is significant in e-commerce and operations management. The study systematically explores the interplay between product returns and seller restrictions as a return policy by developing a dynamic model for online platforms. It identifies and quantifies the impacts of various return types on platform performance, offering insights into the effectiveness of policies targeting sellers with high return rates. This study advances academic knowledge by comparing model outcomes with real-world data from a leading Iranian e-commerce platform. It provides practical guidance for improving operational practices, equipping stakeholders to navigate the complexities of the online retail landscape effectively.

2. Literature Review

Digitalization and advancement in related technologies are driving significant innovation in the retail industry (Mostaghel et al., 2022). The Internet has become a pervasive way for businesses to sell and distribute commodities to consumers; this has attracted the attention of researchers in the operations, logistics, and supply chain management fields (Griffis et al., 2012). With the surge of e-commerce, traditional retail sales and online sales now fiercely compete; notably, online prices are 9-16% lower than those found in brick-and-mortar stores, as evidenced by prior research (Ramcharran, 2013; Prashar et al., 2015). The ratio of online retail sales to total retail sales in the US rose from about 3% in 2002 to more than 6% in 2008: online retail stores have shown substantial growth despite the recession. While most physical retailers had trouble making enough sales, online retailers achieved 11% annual sales growth in 2009 (Griffis et al., 2012). This trend has continued in recent years. During the Covid-19 crisis, the pace of change in e-commerce growth has markedly accelerated. The pandemic prompted consumers to transition from in-store shopping to online platforms, compelling retailers to adjust and establish a competitive online presence (Ghandour et al., 2023). Global shopping volumes surged from February 2020 to April 2021, leading to a 35% increase in the online retail market capitalization (Bradley et al., 2021). In 2022, the US National Retail Federation stated that online sales, a crucial but challenging source of growth for retailers, make up about 25% of US retail sales (Karlsson et al., 2023). There are two main reasons for this: First, the number of internet users has grown significantly in the past decade; second, the proportion of internet users who buy things online has increased (Griffis et al., 2012). Consequently, the authors witness a surge in innovative retail business models to meet heightened customer expectations (Mostaghel et al., 2022).

One of the major challenges that the online retail industry faces is return management (Griffis et al., 2012), which refers to handling customer reviews, complaints, and product returns. When consumers consider buying a product online, they often assess the risk associated with their decision. This risk can be financial (e.g., wasting money on an unsatisfactory product) or psychological (e.g., regret after a purchase). Online consumers often lack the opportunity to physically examine the products before purchasing them (Dholakia et al., 2005), which makes product evaluation more difficult and increases the likelihood of returns (Peck & Childers, 2003). As online sales continue to rise, especially in the post-Covid era, product return rates exhibit a similar trend (Karlsson et al., 2023). Based on a report published by the National Retail Federation of the US and Retail Appraisal in 2021, in 2020, US consumers returned $428 billion worth of products, which accounted for about 10.6 percent of the total US retailer sales that year, and this was a 64.6 percent increase compared to the previous five years (Li et al., 2022). According to Ambilkar et al. (2022), online returns are expected to reach $7 billion in 2023.

Product returns, in particular, pose a significant problem for online retailers, resulting in a loss of 3.8% of profit per year (Petersen and Kumar, 2010). In 2020, product returns resulted in an estimated 16 million tons of CO_2 and 5.8 billion pounds of waste, and the cost for an online retailer to process a $50 product return was estimated at $33 (Ambilkar et al., 2022). Therefore, it can be seen that consumer product returns significantly impact the industry and society (Karlsson et al., 2023).

Therefore, given the vital importance of handling product returns, especially considering pricing, demand, and product quality uncertainties, effective return management is crucial for businesses (Ambilkar et al., 2022). Managing product returns, developing strategies, and designing product return policies are some of the most important issues the online retail industry should consider. According to a survey, 87% of supply chain managers considered return management important or very important for their organization's operational and financial performance (Griffis et al., 2012).

In 2002, Rogers et al. emphasized that a firm's returns management capabilities can strategically enhance the overall performance of the company. Many recent studies have delved into returns management from a strategic standpoint, examining its impact on overall company performance (Karlsson et al., 2023). Rokonuzzaman et al. (2021) have also shown that retailers have the opportunity to strategically shape their return policies to boost customer confidence and foster loyalty to their stores. Recent empirical research examining the impact of various factors on consumers' digital shopping experience also reveals that implementing a robust return policy significantly enhances online shopping, leading to increased customer loyalty and repeat purchases (Patro, 2023).

Russo et al. (2018) identified specific return practices that contribute to customer satisfaction and align with broader business objectives. Interestingly, they found instances where customer satisfaction remained high despite equally high return rates. Therefore, it can be seen that return policy affects customer buying intention and return behavior (Abdulla et al., 2022) and, as a result, sales and profitability (Karlsson et al., 2023). The Cue Diagnosticity Framework also suggests that consumers use various cues to evaluate a retailer, one of which is their return policies (Rokonuzzaman et al., 2021). Return policies can influence customers' willingness to buy because they may opt for other sellers with more permissive return policies.

In another study, Son et al. (2019) have shown that return amounts do not harm order amounts, and a high amount of returns does not necessarily mean lower profits. They demonstrate that within the low- and medium-price segments, returns positively affect order values, underscoring the significance of adaptable return policies. However, for high-priced items, returns do not notably affect order amounts, implying that dissatisfied consumers in this category might not make repeat purchases from the same brand.

The literature reviewed in this paper highlights the importance of effective return management within the supply chain for achieving organizational success. Ambilkar et al. (2022) argue that information transparency is a key to improving product return management. By providing clear and detailed product information, companies can enhance the efficiency of their return processes (Ambilkar et al., 2022). Moreover, a generous return policy can reduce the perceived risk of online purchases and increase the customer's positive attitude toward the store (Rokonuzzaman et al., 2021). Table 1 provides a summary of the reviewed articles.

Table 25. Key Points in reviewd papers

Key Point	Details	References
Strategic Impact on Performance	Effective returns management enhances overall company performance by improving customer satisfaction and loyalty.	Rogers et al. (2002), Karlsson et al. (2023)
Customer Confidence and Loyalty	Retailers can shape return policies to boost customer confidence and foster loyalty.	Rokonuzzaman et al. (2021)
Digital Shopping Experience	Robust return policies enhance online shopping, increasing customer loyalty and repeat purchases.	Patro (2023)
Customer Satisfaction Despite High Return Rates	Specific return practices can maintain high customer satisfaction even with high return rates.	Russo et al. (2018)
Influence on Buying Intentions	Return policies affect customer buying intentions and return behavior, impacting sales and profitability.	Abdulla et al., (2022), Karlsson et al. (2023) Yan et al., 2019
Adaptable Return Policies	Adaptable return policies positively affect order values in low- and medium-price segments.	Son et al. (2019)
Information Transparency	Information transparency is key to improving product return management.	Ambilkar et al. (2022)
Perceived Risk Reduction	Generous return policies reduce the perceived risk of online purchases and increase positive customer attitudes.	Rokonuzzaman et al. (2021)

This paper concludes that product return policies have significant implications for not only the customer-organization relationship and the organizational performance but also the wider industry and society. Given this importance, there is a need for further research on the different types of product return policies and their impact on various outcomes. This paper identifies a gap in the literature and suggests some directions for future research on the return impact.

3. Methodology

This research adopts the System Dynamics (SD) modeling approach, a mixed-methods approach of quantitative and qualitative methods. It provides a powerful method for analyzing and assessing the dynamic properties of large-scale complex systems (Alamerew & Brissaud, 2020). SD modeling can capture the feedback loops, delays, and nonlinearities that characterize complex systems, such as social, economic, or environmental systems (Khadivar et al.,2024). This approach models and simulates the system using a cause and effect diagram, stock and flow diagram, and system dynamic equations. This study identified the key variables that affect the controllable returns of e-commerce platforms. Then, it specified the parameters and equations representing the relationships and interactions among these variables.

The authors used Vensim PLE software to develop and execute our model and validated it by comparing its outputs with historical data. Vensim is a robust simulation software designed to enhance the performance of real-world systems (Ventana Systems Inc., 2023). It offers many possibilities for sensitivity analysis, scenario evaluation, and diagram creation in system dynamics modeling. This article used the graphical interface to draw the causal loop, stock and flow diagrams, and the equation editor to enter the equations and parameters. This study simulated for 100 days, with a time step of one day. This study conducted a sensitivity analysis to investigate the impact of different parameter values on the model behavior. The diagram creation function is also used to generate graphs and tables that illustrate the model results and insights. To provide a clear overview of the research methodology, Figure 1 presents a flowchart outlining our study's key steps.

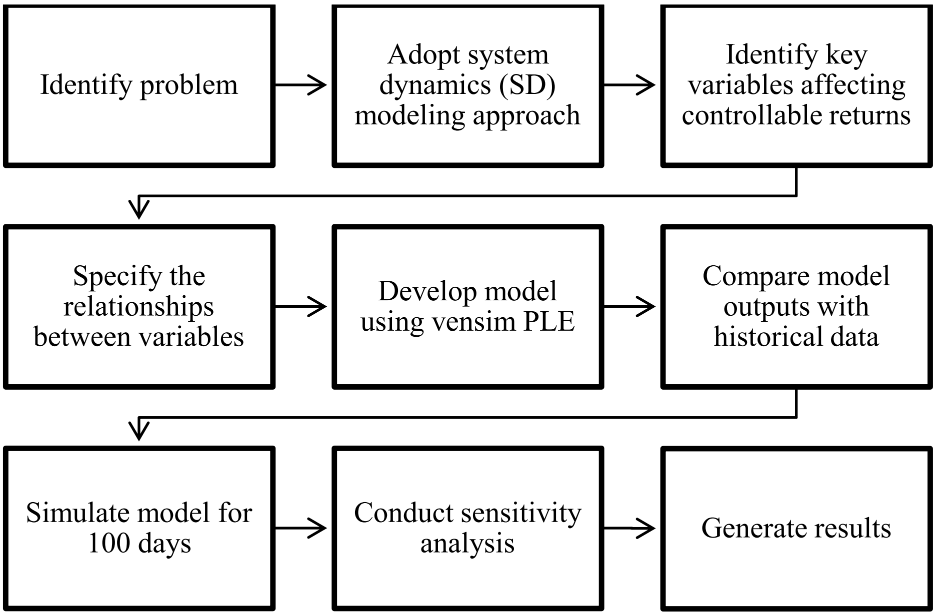

Figure 32. Research methodology steps

3.2. Definition of model variables

Given the multitude of factors at play in the sales system of an online retailer, it is difficult to account for all of them. The boundary of the system under investigation is determined by the study's research question (Yan et al., 2019). The present study has confined the analysis to examining a single return policy, specifically, the policy that imposes restrictions on sellers who exhibit high rates of controllable returns. The impacts of other return policies are not explored within the scope of this research. The variables within the boundary of the system under investigation are delineated in Table 2.

Table 26. Key variables related to the return policy for sellers with high rates of controllable returns

Row	Variable	Description	Unit
1	Controllable return	A type of product return results from the seller's mistakes, such as sending the wrong product, delivering a defective or broken product, or delivering late. Controllable returns are the seller's responsibility and affect the performance score. The product cannot be sold again or can only be sold at a lower price, as well.	Number
2	Product return rate	The ratio of products returned from a day's sale on the platform.	Dimentionless
3	Strict policies in product return processes	The rules and conditions that the platform sets for product return these policies may include seller restrictions, limiting allowable time to return products, asking for reasons and information, deducting shipping fees or penalties, or defining non-returnable items.	Dimentionless
4	The number of restricted sellers	The number of sellers whose access to the e-commerce platform has been temporarily or permanently blocked or limited due to the high return rate of their products by customers.	People

Row	Variable	Description	Unit
5	Average sales by restricted sellers	The average amount of sales of sellers whose access to the e-commerce platform has been temporarily or permanently blocked or limited due to the high return rate of their products by customers.	Number
6	Restricted sales	The total amount of sales of all sellers whose access to the e-commerce platform has been temporarily or permanently blocked or limited due to the high return rate of their products by customers.	Number
7	The number of new sellers on the platform	The number of sellers who have joined the platform and started selling since the start of the day.	People
8	Seller population on the platform	The total number of seller accounts on the platform minus the restricted sellers.	People
9	Total sales	The number of products sold by the sellers or bought by the customers in a period. The number of sales depends on customer demand, seller supply, price, market, and competition.	Number

3.3. Causal loop diagram

Figure 2 shows a causal loop diagram of the model, which consists of three main loops. The first loop (Reinforcing Sales Improvement Loop) is a reinforcing loop that illustrates how restricting sellers with high return rates increases the total sales by improving the average quality of products on the platform. Reinforcing Sales Improvement Loop implies that strict policies and more access denials motivate sellers to sell better-quality products, as the return rate entails a higher risk of reduced profit due to access denial, and the return rate is higher for low-quality products. Therefore, as the average quality of products on the platform increases, buyers become more satisfied and buy more products, which leads to higher sales. Assuming that the return rate is constant, higher sales also result in a higher controllable return rate, increasing the platform policymakers' desire to restrict sellers from reducing the return rate.

The second loop (Quality-Return Balancing Loop) is a balancing loop that depicts how restricting sellers reduces the return rate by enhancing the average quality of products on the platform. Quality-Return Balancing Loop indicates that higher-quality products increase customer satisfaction and decrease their willingness to return products, which lowers the return rate of customers. As a result, the overall return rate of the platform decreases, and the platform policymakers' tendency to increase seller restrictions diminishes.

The third loop (Price-Return Balancing Loop) is another balancing loop that demonstrates how restricting sellers reduces the return rate by raising the average price of products on the platform. Price-Return Balancing Loop suggests that sellers prefer to sell higher-quality products by applying strict policies and increasing access denials, which means higher prices for average platform products. Studies show that cheaper products have a higher return rate, which implies that as the average price of products increases, the return rate and the overall return rate of the platform decrease, which reduces the platform policymakers' desire to increase seller restrictions.

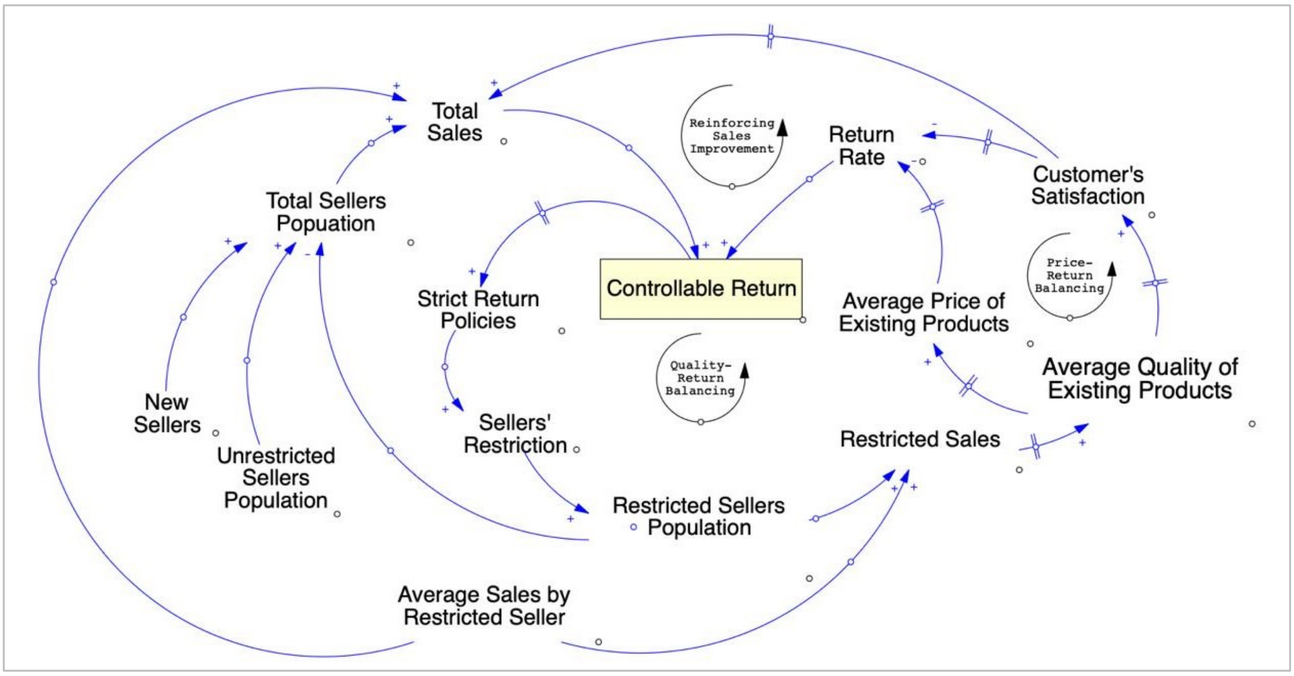

Figure 33. Causal loop diagram of controllable return

The data is analyzed by an e-commerce company, focusing on the controllable return rate of products and restricting sellers. Our regression analysis aimed to uncover any significant associations between these variables and product sales. Figure 3 illustrates that the controllable return rate of products exhibits a significant negative correlation with seller restriction. However, neither of these variables shows a statistically significant relationship with the total number of product sales.

Based on Figure 3, it can be concluded that restricting sellers with high return rates improves product returns but does not substantially impact total sales. This phenomenon can be attributed to the vast product diversity and intense competition on e-commerce platforms. Sellers' entry and exit also become relatively insignificant in the context of the platform's extensive product offerings.

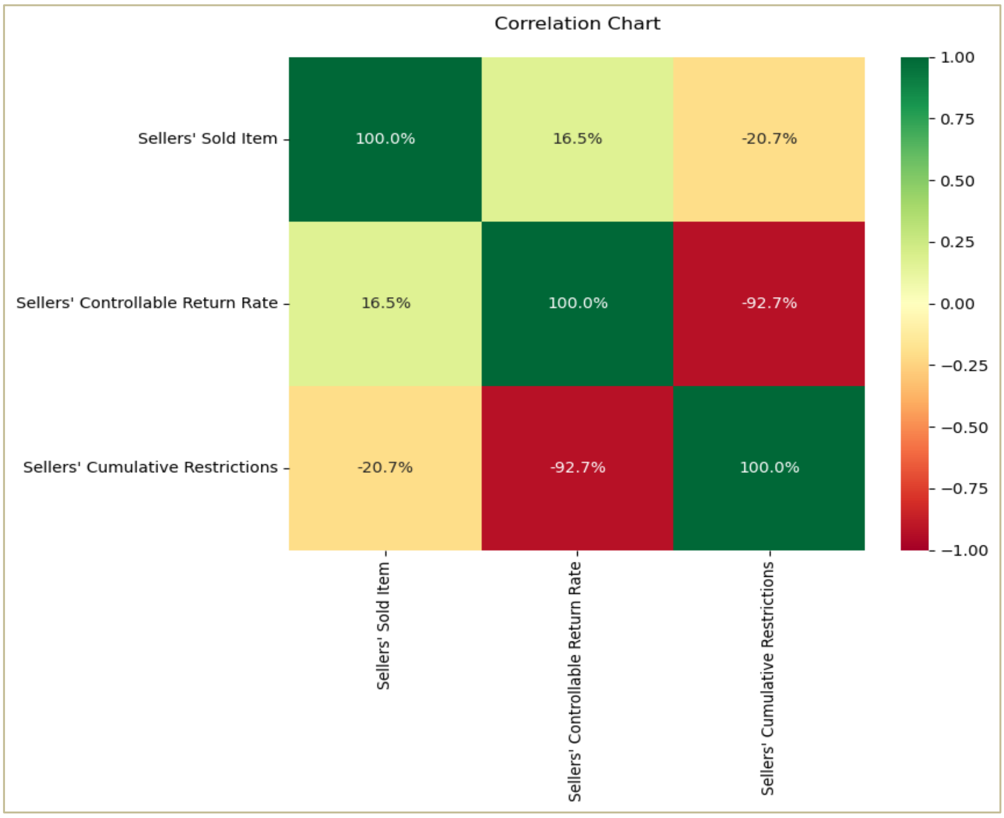

Figure 34. Correlation diagram of three variables: "sold items", "controllable return rate", and "cumulative number of restricted sellers"

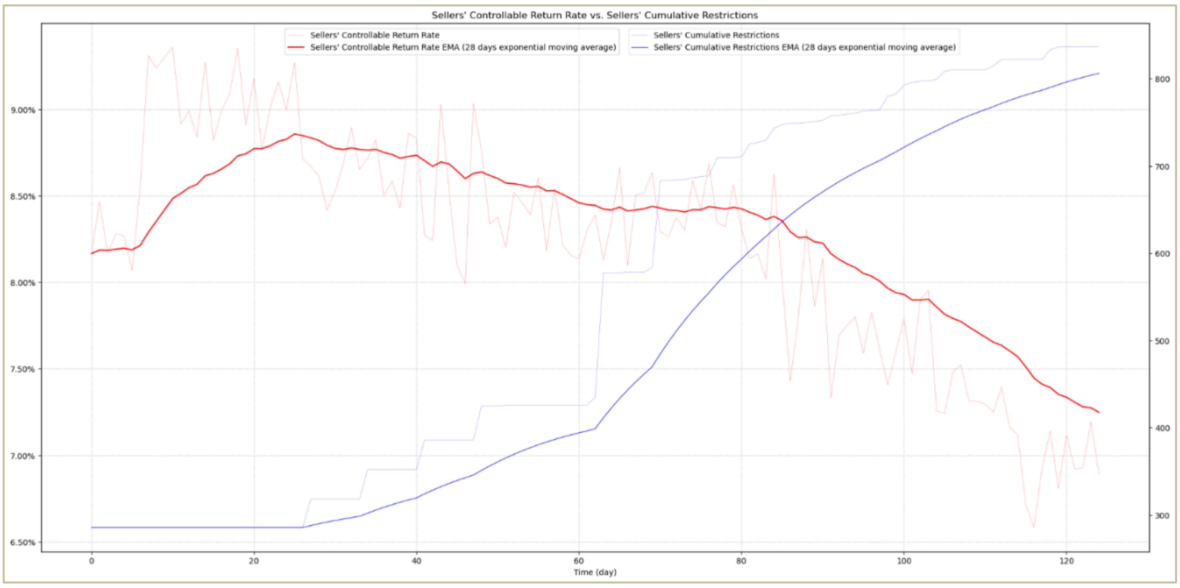

Figure 35. Sellers'controllable return rate changes vs. sellers'cumulative restriction

Furthermore, Figure 4 depicts the trends in the controllable return rate and the cumulative number of restricted sellers over a specific period.

3.4. Model description

The research examines how the policy of increasing access restrictions for sellers with high returns and limiting their sales on the platform affects the amount of controllable returns in e-commerce. As illustrated in Figure 5, the model designed in Vensim PLE software uses equations to describe the relationships between system variables. The key relationship that drives the system behavior is the relationship between the return rate variable and the sales of limited sellers, which was derived from the results of the regression analysis (as shown in Figure 4) in Equation 1:

$$\text{Return Rate} = -5.15*10 \wedge (-9) * \text{Sales of Restricted Sellers} + C \quad (1)$$

where C represents the rate of controllable returns at the beginning of the study. The following equations are presented below:

$$\text{Return} = \int(\text{Increase/Decrease in Return}) \quad (2)$$

$$\text{Increase/Decrease in Return} = \text{Return Rate} * \text{Total Sales} \quad (3)$$

The sales of the entire platform during different periods are regarded as fixed and equal to 200,000 products to simplify the model and aid in its development.

$$\text{Sales of Restricted Sellers} = \int (\text{Increase/Decrease in Sales of Restricted Sellers}) \quad (4)$$

$$\text{Increase/Decrease in Sales of Restricted Sellers} = \text{Average Sales of Restricted Sellers} * \text{Restricted Sellers Population} \quad (5)$$

In order to build the model, it can be assumed that each seller sells 100 products on average per day and that these products will be removed from the market once the seller's restrictions are implemented. The number of sellers subject to restriction varies depending on the return policies of the platform, which may be categorized as either strict, moderate, or permissive.

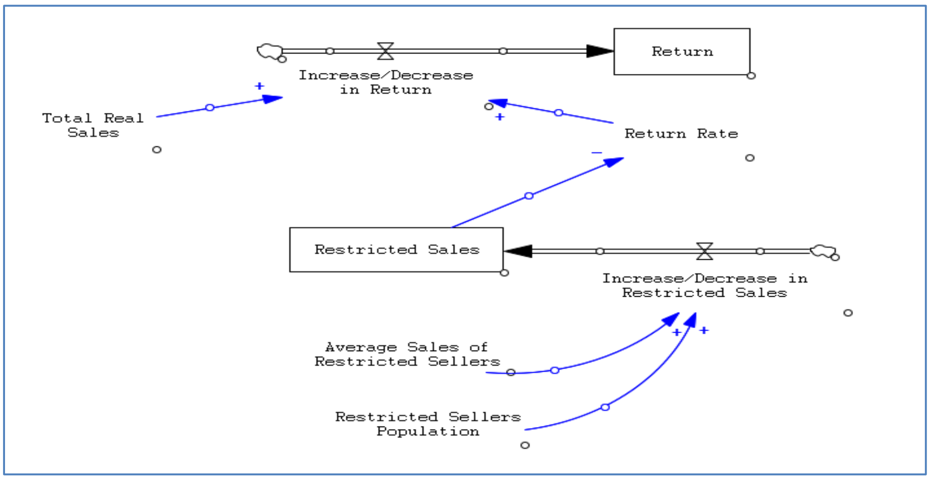

Figure 36. Stock-and-flow diagram, describing the effects of restricting sellers on the returns amount

4. Results

4.2. Model validation

This section aims to validate the model and simulation developed for the study. A multidimensional process is necessary to ensure the model's accurate functioning. This process involves creating problem representations, deciphering logical structures, and exploring mathematical cause-and-effect relationships (Liu et al., 2023; Saghaei et al., 2022). Validation is the systematic process of assessing the reliability and utility of a model. In the context of system dynamics models, validation becomes intricate due to the diverse stakeholders, each with distinct objectives and evaluation criteria (Forrester and Senge, 1980). For a scientific audience, a model's utility lies in its ability to provide insights into the underlying structure of real-world systems, make accurate predictions, and inspire relevant inquiries for future research (Forrester and Senge, 1980).

4.2.1. Test of model boundaries adequacy

The boundary adequacy test assesses the appropriateness of model aggregation and whether the model includes all relevant components (Forrester and Senge, 1980). In other words, this test checks whether the exogenous and endogenous variables are within the defined ranges for the model. The exogenous variables are the inputs determined outside the model, such as seller satisfaction and profit. The endogenous variables, such as quality and price, are the outputs determined by the model. The defined ranges are the minimum and maximum values the variables can take based on the real system and the model assumptions. The results confirm that all variables are within the acceptable range, meaning the model boundaries are adequate and realistic.

4.2.2. Test of model structural verification

Structural verification ensures that the model adequately incorporates the relationships relevant to the research goals (Kaveh Pishghadam and Esmaeeli, 2021). The test results demonstrate that the model is constructed with a systematic methodology and responds appropriately to the changes in the inputs and parameters. The model structure is valid and reliable.

4.2.3. Test of model behaviour under extreme conditions

This examination explores the model's behavior when its inputs are at the boundary conditions: when they attain their minimum or maximum levels (Kaveh Pishghadam and Esmaeeli, 2021). When extreme conditions are considered, the model typically exhibits improvement within the normal operational range (Forrester and Senge, 1980). Zero demand, zero in-process inventories, infinite supply, or negative prices are some examples of extreme conditions. The test aims to assess the robustness and stability of the model under these conditions. The results show that none of the state variables become negative, and the flow of information and materials follows the right directions based on the model assumptions. The model behavior is reasonable and consistent under extreme conditions.

4.2.4. Test of model dimensional consistency

This test involves applying dimensional analysis to the rate equations of a model and verifies the accuracy and consistency of different units of variables (Forrester and Senge, 1980). The results indicate that all variables are assigned to suitable units, and no conflict or inconsistency exists among them. The model dimensional consistency is maintained and verified, as illustrated in Figure 6.

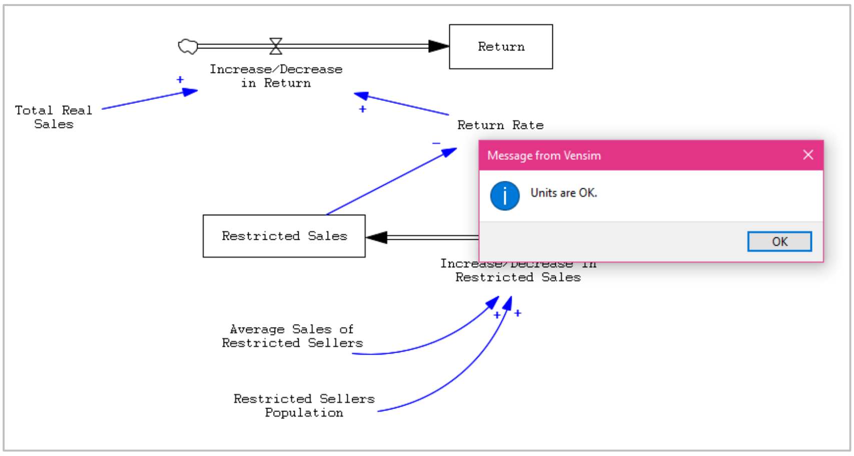

Figure 37. The result of the test of model dimensional consistency

4.3. Sensitive analysis

This section reports the sensitivity analysis results of how the system behaves under different policies. Three scenarios were examined, and Figures 7 to 12 display the analysis outcomes.A) Permissive policy that restricts only one seller on average per day: The sensitivity analysis of this policy indicates that the controllable return amount attains about 311,000 products after

100 days, as Figure 7 illustrates. This is because the return rate (Figure 8) declines marginally from 1.558% on the first day to 1.552% on the hundredth day, which is an insignificant change. Therefore, the total return change rate (Figure 9) stays nearly constant and unchanged at around 3100. Assuming this policy restricts only one seller per day, the restricted seller population remains at one during the period (Figure 10). Based on the assumption that the average number of products these sellers sell is steady at 100 products per day, the restricted sales change rate remains constant at 100 throughout the hundred days (Figure 11). Figure 12 demonstrates that the cumulative number of restricted products reaches 10,000 after the hundredth day, based on the policy of restricting one seller per day.

B) Moderate scenario that restricts 25 sellers on average per day: The sensitivity analysis of this scenario shows that the controllable return amount decreases to approximately 299,000 products after 100 days, as Figure 7 depicts. This is because the return rate (Figure 8) declines slightly from 1.558% on the first day to 1.429% on the hundredth day, about 65 times more than the change in the first scenario. As a result, the restricted sales change rate, as illustrated in Figure 9, also declines from 3,100 products per day on the first day to 2,860 products per day on the hundredth day. Assuming that this scenario restricts 25 sellers per day, the restricted seller population remains at 25 during the period (Figure 10), and based on the assumption that the average number of products sold by these sellers is constant at 100 products per day, the restricted sales change rate also stays constant at 2,500 products per day throughout the hundred days (Figure 11). The cumulative number of restricted products reaches 250,000 after the hundredth day, as Figure 12 indicates, based on the scenario of restricting 25 sellers per day.

C) Strict scenario that restricts 50 sellers on average per day: The sensitivity analysis of this scenario shows that the controllable return amount decreases to approximately 286,000 products after 100 days, as Figure 7 depicts. It is lower than the controllable return amount of both the first and second scenarios. This is because the return rate (Figure 8) decreases significantly from 1.558% on the first day to 1.3% on the hundredth day, about 130 times more than the change in the first scenario. As a result, the total return change rate (products per day) (Figure 9) also decreases from 3,100 on the first day to 2,600 on the hundredth day. Assuming this scenario restricts 50 sellers per day, the restricted seller population remains at 50 (Figure 10). Based on the assumption that the average number of products these sellers sell is constant at 100 products per day, the restricted sales change rate also stays constant at 5,000 products per day throughout the hundred days (Figure 11). Figure 12 indicates that the cumulative number of restricted products reaches 500,000 after the hundredth day, based on the scenario of restricting 50 sellers daily.

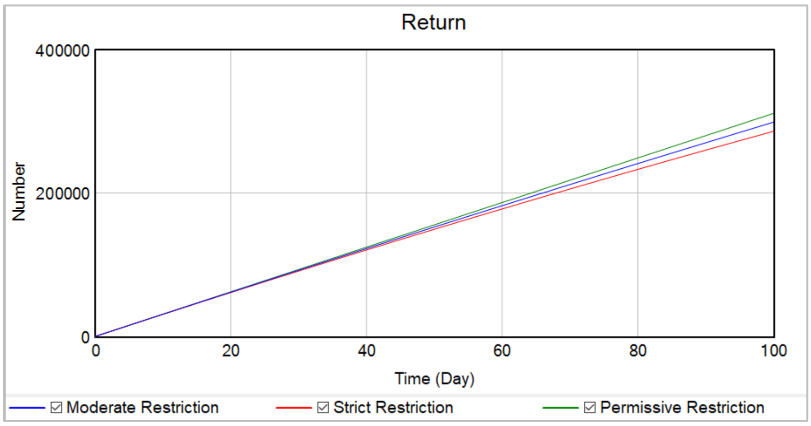

Figure 38. The number of controllable returns, under three scenarios of seller restriction policies

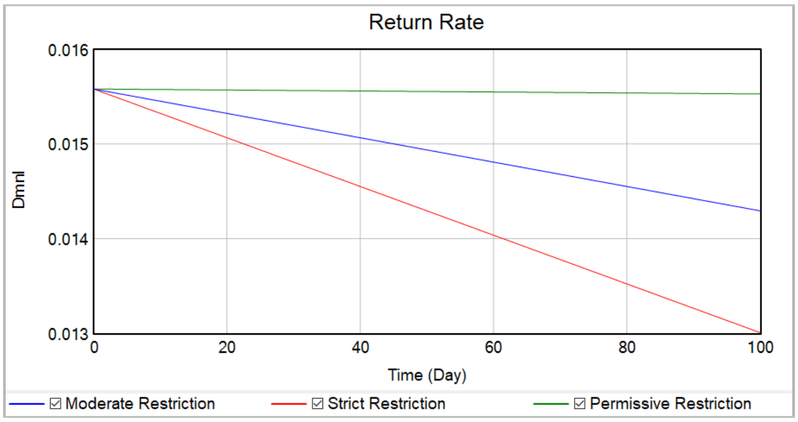

Figure 39. The controllable return rate, under three scenarios of seller restriction policies

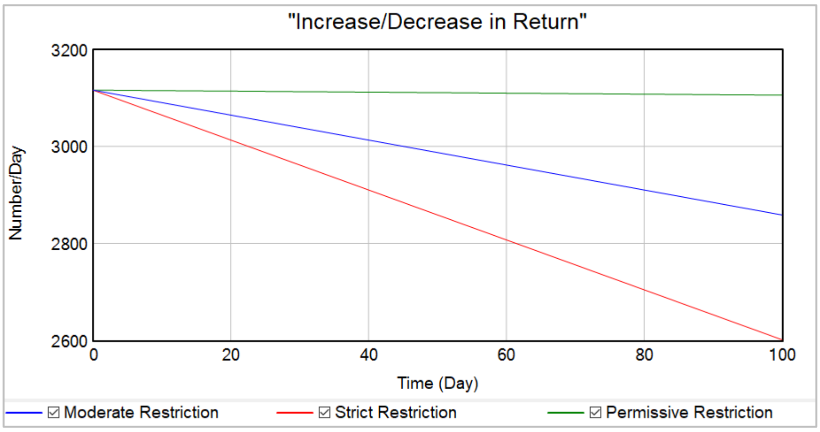

Figure 40. Changes in controllable return rate, under three scenarios of seller restriction policies

Figure 41. Restricted seller population, under three scenarios of seller restriction policies

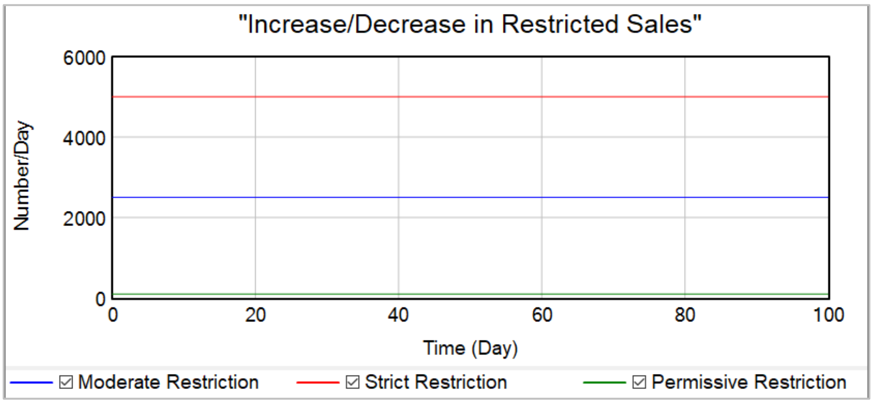

Figure 42. Changes in restricted sales, under three scenarios of seller restriction policies

Figure 43. Cumulative number of restricted sales, under three scenarios of seller restriction policies

5. Conclusion and suggestions

E-commerce platforms grapple with managing product returns, which impact customer satisfaction, operational efficiency, and financial outcomes. The controllable return dynamics model offers a framework to address these complexities. This research delves into the controllable return dynamics model within the e-commerce landscape. Our findings demonstrate that implementing a policy of increased restriction for sellers with high sales returns significantly reduces the overall number of returns. Notably, stricter restriction policies lead to a more rapid decline in controllable returns. Consequently, the authors recommend adopting this policy as a proactive measure to improve overall platform performance.

Future research can extend the model to explore the impact of increased seller restriction on customer satisfaction, seller experience, cost savings, and revenue gains. Additionally, this modeling can be developed by considering supplementary variables related to product return policies, such as varying customer return costs, adjusting the time window for accepting returned goods, and identifying and labeling customers with high return rates. This approach can provide insights into sales variables, return rate, customer satisfaction, seller satisfaction, and e-commerce profit. In conclusion, the controllable return dynamics model provides insights for e-commerce platforms. By strategically managing restrictions, platforms can optimize returns while maintaining positive user experiences and financial health.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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Journal of Systems Thinking in Practice
JSTINP, *QUARTERLY*
Homepage: jstinp.um.ac.ir
Online ISSN: 2821-1669, Print ISSN: 2980-9460
Review Article
DOI: 10.22067/JSTINP.2024.87163.1095
JSTINP 2024; Vol. 3, No.4

Factors Affecting the Effectiveness of Scientific Elites in Society: A Systems Thinking Approach

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How to cite this article

Moubed, M., 2024. Factors Affecting the Effectiveness of Scientific Elites in Society: A Systems Thinking Approach. *Journal of Systems Thinking in Practice*, 3(4), pp.82 -101. doi: 10.22067/jstinp.2024.87163.1095.
URL: https://jstinp.um.ac.ir/article_45728.html.

ABSTRACT

Elites, a distinct group by a privileged status, must positively impact their society. In developed countries, they can be found to contribute to improvements at national and global levels and cause more value added in different areas. However, in countries with a low elite quality rating, they cannot influence society as much and usually tend to immigrate from the country. This paper uses a systems thinking approach to model the influences and effectiveness of elites in society and the main parameters that can improve them. The whole system in this paper consists of the family system, education system (school and university), and society. The study shows how elites can influence society through causal maps and causal loop diagrams. In the following, the MICMAC technique is used to find the most important and influencing variables and categorize them into three main groups: The determinant variables are mostly influencing than dependence, for example, invention and innovation. Dependency on factors, including elites' drive for work, is more dependent than influencing. The autonomous variables have low influence and low dependence. The whole model's variables diagram shows the system as a stable, meaning its results can be predicted accurately with a degree of assurance.

Keywords

Elite, Effectiveness, Influence, Systems thinking, System dynamics, MICMAC.

Article history

Received: 2024-03-07
Revised: 2024-08-28
Accepted: 2024-09-23
Published (Online): 2024-12-20

Number of Figures: 9 **Number of Tables: 3** **Number of Pages: 20** **Number of References:18**

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1. Introduction

"Elite" was first used in the seventeenth to describe a particular excellence in a social group (Bottomore, 1964). Later, the argument of "elite influence" was introduced, which means elites are defined by their performance rather than other positions such as family or wealth. Also, influencing elites is defined by four characteristics:

- Flexibility: They do not have a fixed attachment to a particular position and easily shift their roles.
- Informality: They easily replace the formal structures whenever they are not beneficial.
- Mobilizing entities: They mobilize consultancies, think tanks, and NGOs.
- Connector: They have a connector role in different ecosystems and networks (Wedel, 2017).

As a special group, scientific elites, comprising researchers, academics, and thought leaders, have become increasingly significant in shaping public discourse, helping technological advancements, collaborating in innovative research, and influencing policy decisions. These elites mainly come from universities and academic places and can be masters, PhDs, postdoc students, graduates, or faculty members. They can bridge the gap between scientific concepts and society needs. Understanding the mechanisms through which these elites exert their influence is critical for society to maximize effectiveness.

In the Elite Quality Report for 2023, Iran is ranked 140 of 151 studied countries. In this report, Iran's place in the power and value creation matrix in the fourth quadrant is described as striving elites that show a bad situation and need to be considered. Since improving the place of elites in their power needs much attention from the political structure and is more complicated, value creation is considered the main subject. The place of Iran in the elite quality matrix shows that elites cannot create value on the whole, which may be one of the reasons for the miserable trend of brain drain. Therefore, the problem is defined as understanding the systems and mechanisms that can help the scientific elites in Iran to be more effective for their society. The entire system and its subsystems must be considered, along with the primary variables and their interactions, to identify the systems and mechanisms. In this study, the scientific elites were considered, the ones who originate from universities and academic centers, for example, postgraduate and PhD students, the graduated ones, and faculty members in all fields (except medical sciences).

This paper represents a novel approach to studying the effects of scientific elites on society through a systems-thinking perspective. To the best of the researcher's knowledge, no prior work has utilized this approach to explore the dynamics and complexities of the scientific elites' influence on society. This research aims to uncover the interconnections and feedback loops that shape the interactions between different parameters of elites' effectiveness. This innovative perspective allows for a more comprehensive understanding of how scientific elites disseminate knowledge and engage with various societal factors, ultimately affecting public discourse and decision-making. The effects of these elites on the society and the processes are derived from elites and experts who work with elites in INEF[1] (Yazd branch) using causal maps. Then, the causal maps were turned into system dynamics models by a systems thinking approach, and finally, by a MICMAC[2] algorithm, the most influencing factors were identified.

The rest of the paper is organized as follows: The next section is about the problem statement and main assumptions, followed by a review of related research. Section 3 states the research methodology, and its process. Section 4 describes the steps of methodology including causal maps and loops, model validation, MICMAC algorithm and variable categories, and the results of each step. In the final section, the main results of the research are described, and some recommendations for future researchers are made.

2. Literature review

The term "elite" is rooted in Pareto's work on distributing wealth; however, today, it goes beyond its roots in classes and describes different actors in a society. As a definition, elites are "a distinct group within a society that enjoys a privileged position and exercises decisive control over the organization of society". It does not require that elites are wealthy or members of the ruling class, but it shows that they have a measurable impact on development outcomes (Casas and Cozzi, 2023). While national wealth is a determinant of growth, it can result from elites' actions; they can initiate and motivate institutional changes that drive development (Mistree, 2013). Therefore, an important question here is how elites use their influence for society's improvement.

Prior research has examined the role of elites in economic development. Amsden et al. (2012) used case studies from South Africa to China to analyze elites' engagement in economic development, employing economic modeling, theoretical analysis, social research, and program evaluation (Amsden et al., 2012).

In the field of sociology, studies have explored the origins, education, and formation of elites (Vergara, 2013), such as Korolczuk's (2023) examination of the influence of elites in shaping

[1] Iran National Elite Foundation
2 Matrice d'Impacts Croisés Multiplication Appliquée à un Classement

 DOI: 10.22067/JSTINP.2024.87163.1095

civil society organizations in Poland (Vergara, 2013). A study in China has investigated the social origins of scientific elites, defining members of the Chinese Academy of Sciences as the country's scientific elite (Korolczuk, 2023).

This paper focuses on a specific group of elites – the academic and scientific ones from universities and research centers, excluding medical scientists. As UNESCO defines, science is a significant collective endeavor that improves people's lives (Cao, 1999). Therefore, scientific elites can serve societies in various ways to enhance their quality of life.

One key impact of scientific elites on society is through educating students and young elites, which can occur in research teams and through research projects. Feldman et al. (2009) found that apprenticeship is an effective tool for research education based on their study of an interdisciplinary research project (Feldman et al., 2009). Another area of elites' influence is their participation in government decision-making, such as serving on advisory boards, committees, and panels (Feldman et al., 2009). However, a 2019 survey identified tensions between policy-makers and scientists, with the policy-making system primarily shaped by a techno-scientific perspective rather than a socio-technical one (Gianos, 1974). Boberg-Fazlig et al. (2023) explore the role of agricultural elites in transitioning Denmark from a post-Malthusian era to a modern economic growth regime. They played a significant role in introducing new agricultural methods, including centralized dairy production, eventually leading to the establishment of cooperative creameries throughout Denmark (Boberg-Fazlic et al., 2024).

At the time of this paper, INEF is responsible for recognizing, organizing, and supporting elites through various means, such as funding research and providing grants to researchers. However, this foundation's administrative and highly bureaucratic structure has led to inefficiencies in many of these processes (Smallman, 2020; Boberg-Fazlic et al., 2024). Another study conducted within INEF, which utilized soft systems and cognitive mapping approaches, developed a model for the factors affecting the life cycle of elites. This research identified three groups of factors influencing the life cycle of elites within INEF: (1) structural factors, including both facilitating and leading elements; (2) behavioral factors, encompassing personal characteristics and human values; and (3) contextual factors, consisting of cultural, ethical, and social elements (Yari et al., 2023).

In summary, it can be concluded that scientific elites impact their societies through different mechanisms, from teaching and growing students to making wealth through their own companies, helping others to develop their businesses, or solving their problems. While the literature provides some insights into the impact of scientific elites, there is a lack of research examining the underlying mechanisms of these influences, especially from a systems-thinking perspective. This study aims to address this gap by using a system dynamics approach to model the factors affecting the effectiveness of scientific elites in society. In systems thinking and related tools, many previous works have been done on other subjects; for example, Ruhani et al. (2015), a System of Systems (SoS) approach designed some green public policies, Rostami et al. (2020) used interpretive structural modeling (ISM) and MICMAC analysis to study the induced demand of health service and its effects (Golshahi et al., 2022).

3. Research methodology

Elites and their influences and effectiveness in society are complex systems of different social sub-systems (Figure 2), with many variables that seem too complex to quantify. Therefore, this paper utilized a systems thinking approach to model this complex phenomenon. The research began with a literature review and semi-structured interviews with experts working with elites at the INEF, Yazd branch, during 2023. These interviews helped to extract the main indicators and variables influencing the effectiveness of elites (Table 1).

Using the Decision Explorer tool, the causal mapping technique was used to illustrate the links between these factors. The experts collaborated to visually represent the causal linkages between the identified variables as a causal map (Figure 3).

Next, the researchers used Causal Loop Diagrams (CLDs) to model the various subsystems and identify the main feedback loops within the system. It allowed them to understand the dynamic interactions between the elements and pinpoint the external variables that can impact these loops.

Finally, the study utilized the MICMAC technique and the associated software application to categorize the main variables affecting the system. This analysis helped to determine the most influential variables and assess the system's overall stability.

The step-by-step process of this research approach is summarized in Figure 1.

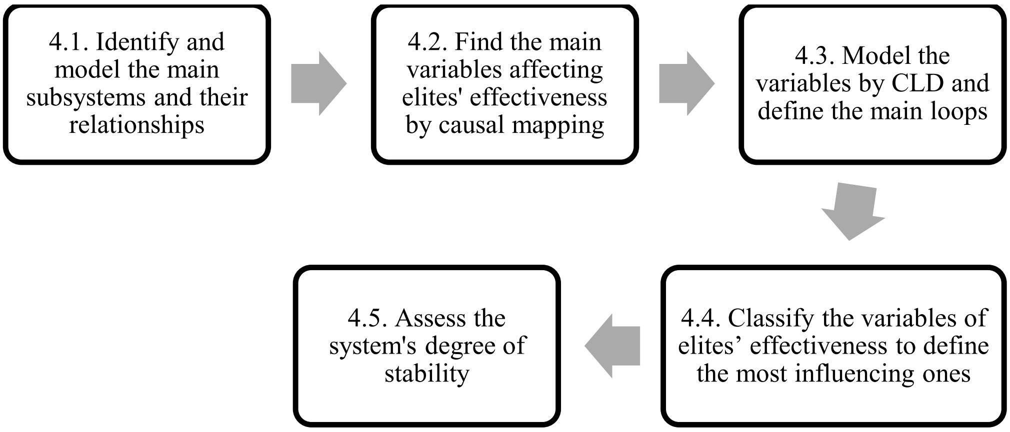

Figure 44. The research process

4. Results

In this part, the research methodology is explained step by step, and the results of each part are described.

4.1. Identify and model the main subsystems and their relationships

The goal of designing a system model for elites' effectiveness is to recognize the dynamic relations between different actors and variables contributing to the system to find the leverage points to maximize their effectiveness. Understanding the subsystems and their relationships is necessary before attempting this goal. These main subsystems and their relations are illustrated in Figure 2. In this model, the family system is the creator of the culture and personal behaviors of students in schools and higher education systems. The output of the school system is students for the higher education system and graduates for society. The higher education system also provides research services for society, besides the graduates that serve society.

Conversely, society also provides opportunities for students and faculty members in the higher education system to work and gain experience. Of course, the society itself includes the education and higher education system, but these two parts are separated for analysis. The higher education system provides teachers for the education system and schools. Some higher education graduates and faculty members can serve the scientific centers abroad. This relationship is two-way; it means that these centers provide graduates or faculty members with access to the internal higher education system. Research, including articles, books, and research reports, are sent from the higher education system to science centers, and credit and ratings from these centers are given to the higher education system.

 DOI: 10.22067/JSTINP.2024.87163.1095

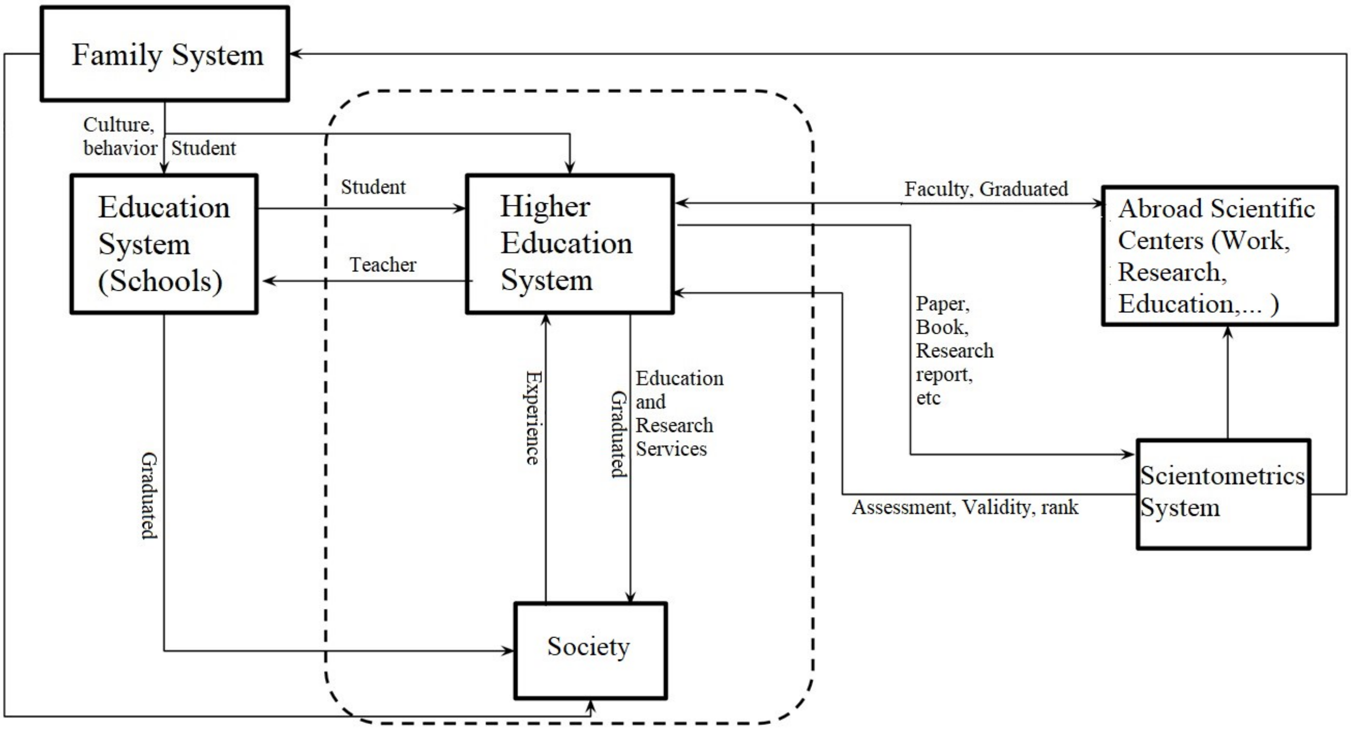

Figure 45. The relationship between the main sub-systems of the elite effectiveness system

4.2. Find the main variables affecting elites' effectiveness by causal mapping

A causal map is a network of links (arcs) between variables, for example, A and B that means someone believes A has an influence on B. Ackermann and Alexander (2016) exploring causal mapping, show its strengths, weaknesses, and opportunities to be used in systems thinking approaches and in complex projects (Teymourifar and Trindade, 2023). This paper extracted the mind maps during semi-structured interviews with elites and experts who worked with INEF in the Yazd branch during 2023. The variables were initially extracted from the literature review and the strategic plans of INEF and reformed into causal maps during interviews. The final achieved causal map is depicted in Figure 3, and the main variables are defined in Table 1.

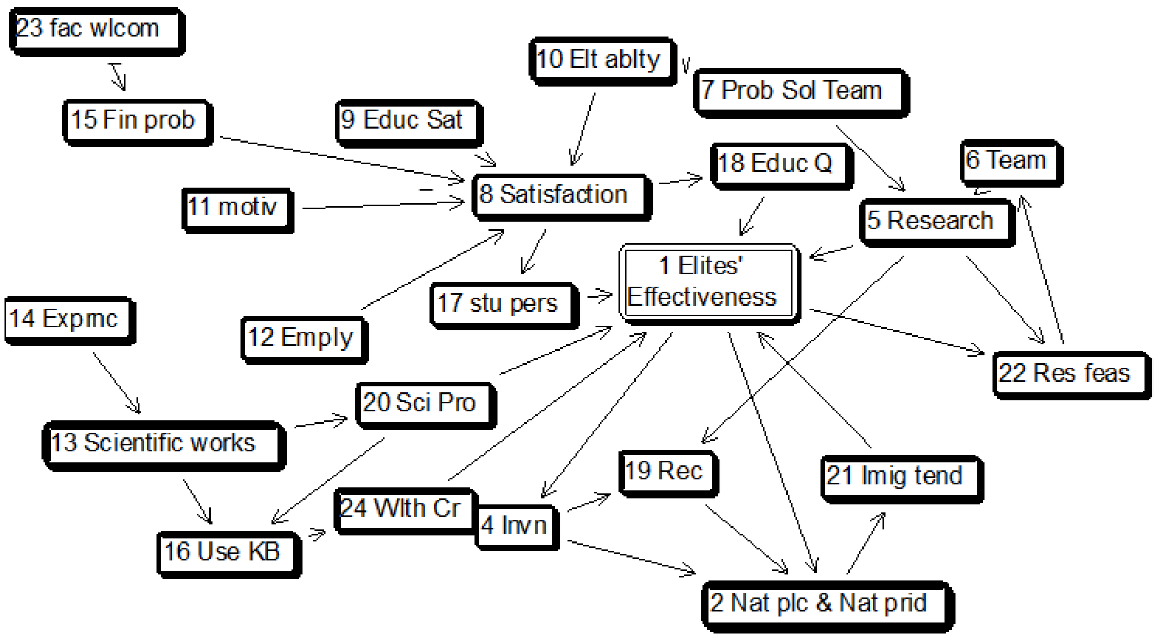

Figure 46. Final causal map for variables affecting elites' effectiveness

Table 27. Variables definition and their symbol in model

Variable description	Symbol
Accessing powerful teams for research	Team
Cooperation in problem solving teams of enterprises and government	Prob.Sol Team
Elite's satisfaction by the education system provided for him/her	Educ Sat
Elites' abilities for scientific works	Elt ablty
Elites' motivation to work	motiv
Employment of elites	Emply
Experience in scientific works	Exprnc
Financial problems that occur for elite	Fin prob
Inventions and innovations by elite	Invn
Knowledge that used in knowledge enterprises	Use KB
National pride (to be pride of their country and origin)	Nat prid
Persuade students and young elites for scientific work	stu pers
Quality of educations provided by elites for students	Educ Q
Recognition and knowing elite by elites' society	Rec
Researches (for government/ companies to solve their problems)	Rsch
Science production (books, research reports, papers, etc.)	Sci Pro
Tend to immigrate from the country	Imig tend
The feasibility of elite (time and facilities) to do researches	Res feas
The place of country in international rankings	Nat plc
Using INEF facilities (like subsidy)	fac wlcom
Wealth creation	Wlth Cr

4.3. Model the variables by causal loop diagrams

A causal loop diagram (CLD) is developed to show the interaction between components of subsystems and the main feedback loops of system behavior. In these diagrams, the relationship between variables A and B can be positive (+) or negative (-), which means a similar or inverse change in variables. The main variables of CLD are derived from the causal map in Figure 3. In order to be clearer, the subsystem loops are described separately in the following sections. These loops are developed during interviews with elites and experts in INEF to understand the direction and relationships between variables.

4.3.1. Research system and loops

Researching and finding responses to different questions are among the main responsibilities of an elite. Here, the main variables that affect research and their consequences are developed in a CLD (Figure 4). A group of reinforcing loops in the CLD links research to other variables and reinforces research behavior for elites. These loops, as shown in Figure 4, are named as:

Loop 1- Research quality: By doing more research, an elite gets more experience and, therefore, can do better research in the future.

Loop 2- Research team: With more research, more innovations and inventions will occur, which makes the elite more recognized. Therefore, he/she can access better teams, which will result in more research.

Loop 3- Innovation and invention: With more inventions and innovations, the percentage of them used in knowledge organizations will increase, creating more wealth. It will decrease the elite's financial problems, and therefore, she/he can do better research again to increase innovations and inventions.

Loop 4- Science creation: Research results in more science creation used in knowledge organizations, creating more wealth that will decrease financial problems again. Like the previous loop, it will increase research again.

Some of the external parameters impacting these loops are:

- Governmental support is needed to launch knowledge enterprises to use the science and knowledge produced by scientists in these companies.

- Improving the intellectual property laws that persuade innovations and inventions and strengthening the relationship between them and launching knowledge enterprises.

- The research rules in universities that affect the feasibility of doing research by elites who work there.

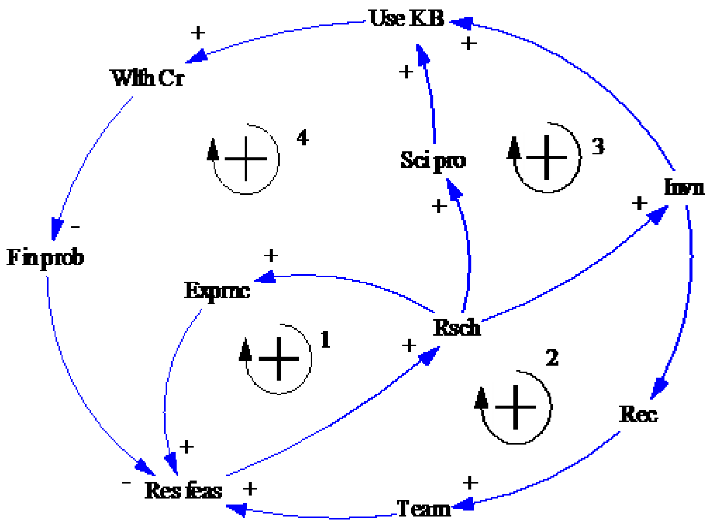

Figure 47. CLD for research

4.3.2. Education loops

Another way for elites to influence society is by educating young students and potential elites, the main circles shown in Figure 5. This graph shows that by educating young elites, they will be persuaded to do better scientific work that can finally improve the country's place in international rankings and national pride. With more national pride, the potential elites' motivation and encouragement for work increases again, and their desire to immigrate from the country decreases; therefore, they use more facilities provided by the INEF. Using more facilities decreases elites' financial problems and improves the quality of their education services, which will encourage young elites again. More elites' persuasion for scientific work will improve their abilities, which will help them find better employment and motivation for work. In this diagram, six reinforcement loops can be seen, and three of them are described here. In order to summarize, the authors used "+" to show the increase, "–" to show the decrease, and "→" to show the result.

Loop 1- Education provided by elites and the consequences for young elites: Education quality → +Students persuasion → +Elites' abilities → +Employment → + Elites' motivation for work → + Using National Elite Foundation facilities → -Financial problems → - Education quality.

Loop 2- Students persuading that empowers itself: Students persuasion → +Elites' abilities → +Students persuasion.

Loop 3- National Elite Foundations' facilities: Using National Elite Foundation facilities → -Financial problems → +Immigration tendency → - Using National Elite Foundation facilities.

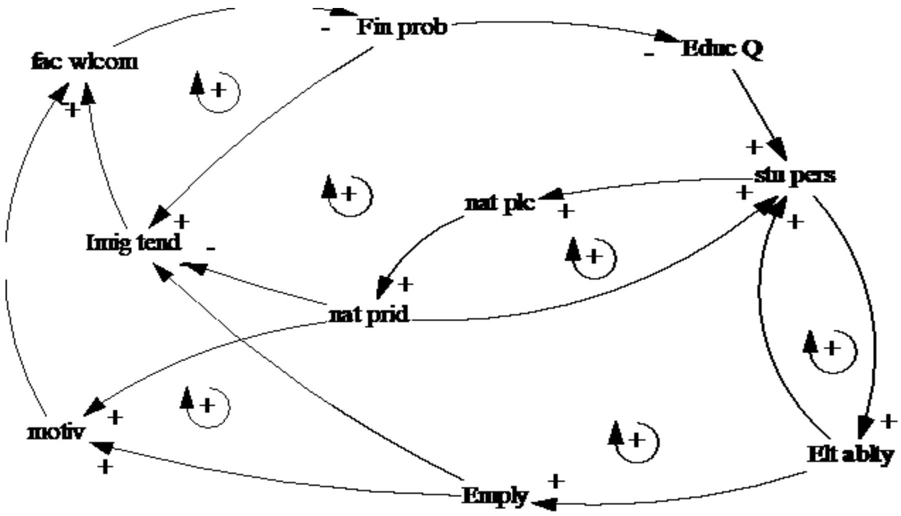

Figure 48. CLD for education provided by elites

Some of the external parameters impacting these loops are:

- Education, training, and empowerment of elites that improve their abilities, their motivation for work, and the quality of training they provide for students.

- Financial support for elites to reduce their financial problems and work with more peace of mind.

- Social satisfaction that affects all the factors, especially increases the elite's motivation to work and the quality of education they provide.

4.3.3. Problem solving loops

Involving elites in solving the problems of institutes (government or private), increases their effectiveness for society. Since the government has more power and influence on other parts of society, these institutes are more important here. The loops of problem-solving are depicted in Figure 6. As shown there, with more motivation from the elites for work, their participation in problem-solving teams will increase, which means more elites' employment, work experience, and better research activities. More research means more science production that can be used in knowledge enterprises, increasingtheir employment and motivation for work. Some of the main reinforcement loops of this model are:

Loop 1- Problem solving teams and employment: Cooperation in problem solving teams of enterprises → +Experience → +The feasibility to do researches → +Doing researches → +Inventions and innovations → +Use in knowledge enterprises → +Employment of elites → +Elites' motivation to work → +Cooperation in problem solving teams of enterprises.

Loop 2- Problem solving teams and motivation: Cooperation in problem solving teams of enterprises → +Employment of elites → +Elites' motivation to work → +Cooperation in problem solving teams of enterprises

Loop 3- Research and recognition: The feasibility to do researches → +Doing researches → +Inventions and innovations → +Recognition → +Access to powerful team for research → +The feasibility to do researches.

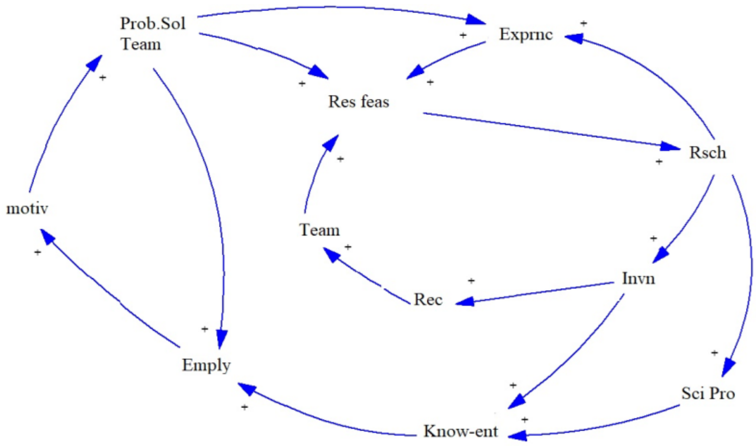

Figure 49. CLD for participating in problem solving teams

Some of the external parameters that impact these loops are:

- Special attention from governmental institutions to use elites in their problem-solving teams.

- Governmental support is needed to launch knowledge enterprises to use the science and knowledge produced by scientists in these companies.

- Elites' social satisfaction affects all the factors, especially the motivation of elites to work and their participation in problem-solving teams and projects.

4.3.4. Combining the loops and model validation

After defining the loops for different parts of elites' effectiveness, all these loops are combined, and the final model is formed. The current model was validated during a discussion with the INEF experts in the Yazd branch. Validating CLD is an iterative process in the project lifecycle (Teymourifar and Trindade, 2023). In this project, the model was also changed according to the feedback provided by the foundation until they approved it. In this process, some new potential relations have been drawn to perform the MICMAC analysis. The final model is shown in Figure 7.

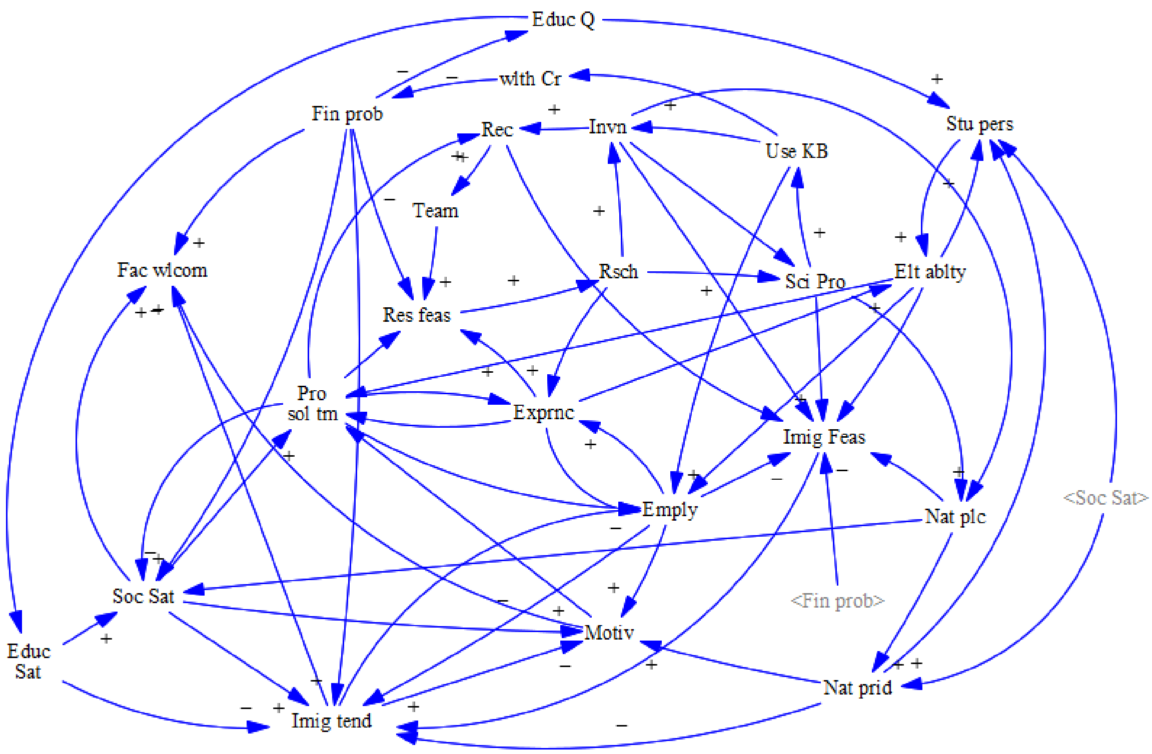

Figure 50. The CLD for elites' effectiveness

4.4. Assess the system's degree of stability and classifying the variables

In previous sections, several factors have been identified that can influence the scientific elites' effectiveness in society. In order to identify the most important and most influential factors, the MICMAC analysis is used (Rostami et al., 2020). Therefore, the model developed in the previous part is used as the input for analysis. The steps of this process are as follows:

4.4.1. Developing a direct relationship matrix

According to the system dynamics model, a direct relationship matrix was developed to collect the experts' opinions about the degree of influence between variables. Data was collected from a group of INEF specialists who had previously participated in identifying the variables to populate the matrix. This statement formed the question: "Can variable A influence directly on variable B?" In this scoring, 0 means no relationship, 1 means a low influence, 2 means a medium influence, 3 means a high influence, and P is a potential influence. Based on the answers gathered here, some of the relations in the causal model have been edited, and the final model has been formed, as shown in Figure 7.

4.4.2. Calculating the influence and dependency of each variable.

At this step, the influence and dependency of each variable are calculated by summing up the numbers in the rows and columns. In this research, the data were entered into a MICMAC application (designed and published by http://www.3ie.org/lipsor), and the influence and dependency were calculated and shown in Table 2. This table is sorted by total influence and shows social satisfaction, financial problems, the elite's abilities, invention, and innovation as the most influential ones. Also, the dependency column shows immigration feasibility, the tendency to immigrate from the country, the employment of elites, the elites' motivation to work, and the persuasion of young elites for scientific work as the most dependent variables.

Table 28. The variables' total influence and dependency

Variable	Total influence	Total dependency
Social satisfaction	14	7
Financial problems	13	4
Elites' abilities	10	5
Invention and innovation	10	3
National place in international rankings	8	4
National pride	8	6
Research	8	3
Knowledge used in knowledge enterprises	7	4
Experience	6	6
Quality of education provided by elites	6	2
Science production	6	4
Cooperation in problem solving teams	5	6
Employment of elites	5	11
Tend to immigrate from the country	5	12
Education system satisfaction	4	3
Elites' motivation to work	3	10
Persuade students and young elites for scientific work	3	10
Recognition by academies and Society	3	2
Research feasibility	3	5
Wealth creation	3	3
Immigration feasibility	2	18
Team accessibility	1	0
Using elite's facilities	1	6

4.4.3. Identification of key variables

A direct influence-dependency matrix was formed after calculating the influence and dependency, as shown in Figure 8. This matrix categorizes the factors studied into three main groups, as shown in Table 3, described in the conclusion.

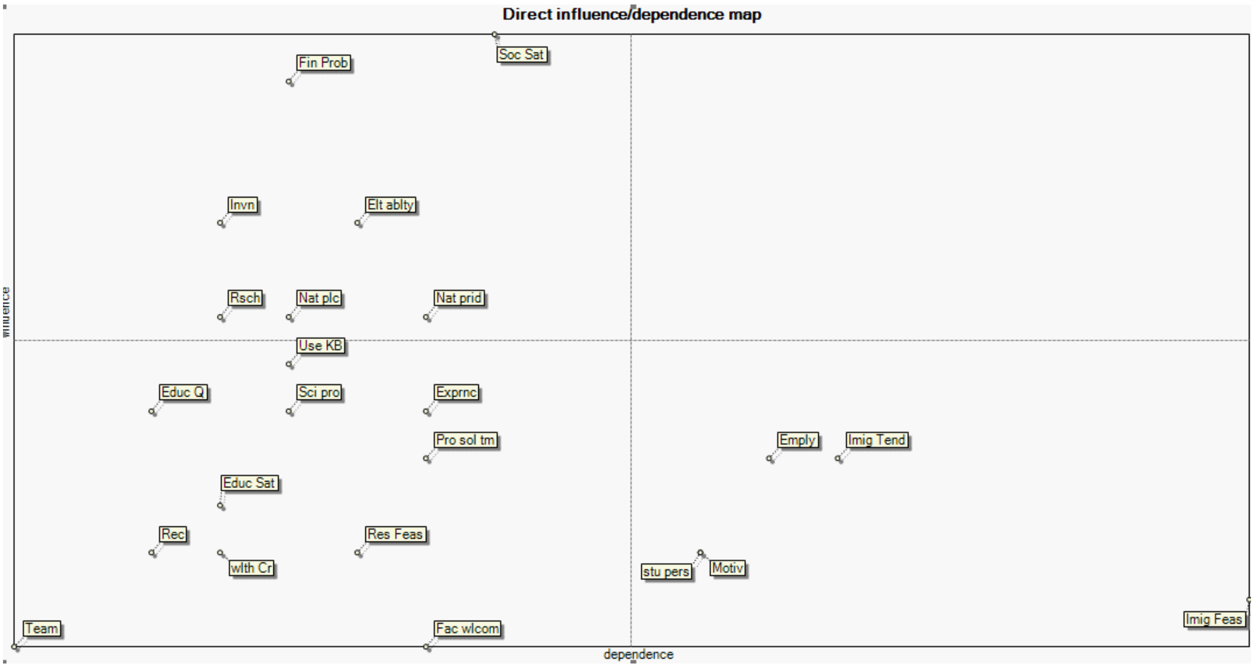

Figure 51. The influence – dependence matrix

Table 29. The three categories of studied variables by their influence and importance

Category name	Description	Variables
1- Determinant/ Influent	High influence and low dependence. The system depends on these crucial variables.	Social satisfaction, elites' financial problems, elites' abilities, invention and innovation, doing researches, national pride, and the place of country in international rankings
2- Depending / result	Low influence and high dependence. Especially sensitive to other variables.	Employment of elites, elites' motivation to work, persuade students and young elites for scientific work, tend to immigrate, and immigration feasibility
3- Autonomous / excluded: 3-1- Disconnected	Low influence and low dependence: near the axis's origin, whose evolution seems to be rather excluded from the system	Access to powerful team for research, wealth creation, research feasibility, using INEF facilities, cooperation in problem-solving teams of enterprises
3-2- Secondary acting	more influential than dependent. located quite above the diagonal.	Experience, quality of education provided by elites, education system satisfaction

4.5. Assessing the system's degree of determination

In order to assess the level of stability of the elites' system, the Figure 9 model was used. According to the matrix obtained in Figure 8 and the model of stability, since elites' system points spread along the axes and the matrix is L-shaped, it is determined (stable). It implies that the system's reaction to a pulse in variables can be predicted with a degree of assurance.

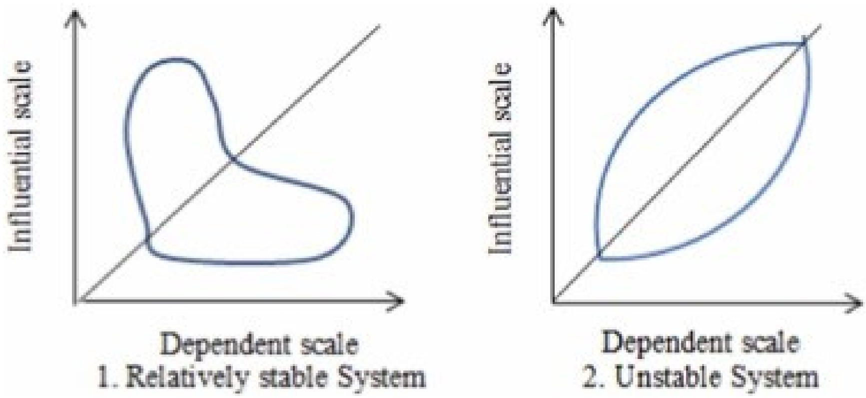

Figure 52. Shape of the system and its stability (Rostami et al., 2020).

5. Discussion and conclusion

The main problem of this paper was to find the variables that can influence the effectiveness of scientific elites in society. First, the main subsystems and the system boundary were defined to define the systems that affect this group of elites. In order to realize the dynamics of elites' subsystems, a systems thinking approach and system dynamics tool were used. Firstly, the causal map was used to determine the influencing variables and their effect. Then, system dynamics and Vensim software defined the main loops of elites' effectiveness in society and developed the model of variables. In the next step, the main influencing and dependent variables were defined by a MICMAC analysis and then categorized into three main groups. The total system is stable, as the matrix of variables finally shows. Since the system of elites' effectiveness is stable, its performance can be predicted with some certainty. Here the research shows "social satisfaction", "elites' financial problems", "elites' abilities", "invention and innovation", "doing research", "national pride", and "the place of the country in international rankings" as the crucial variables. It implies that an improvement in these variables can influence the scientific elites' effectiveness. These crucial variables, such as social satisfaction, national pride, and the place of country in international rankings, are more complicated and need much attention from social, economic, scientific, and political systems. The crucial variables INEF and universities can influence are elites' financial problems, abilities, and research. Universities can improve students' abilities for work and research and persuade them to do research. Also, financial programs like scholarships, grants, loans, work-study programs, food and meal plans, housing, and textbook assistance can be offered by universities and INEF to help elites with their financial problems.

The model categorizes "employment of elites", "their motivation for work", "their persuading of students and young elites", "tendency to immigrate", and "immigration feasibility", which are mostly sensitive and not influential. It means that directly addressing or attempting to manipulate these variables may not yield the desired results, as they are likely the consequence of other variables and the whole system. By understanding and targeting the root causes, the model implies that the desired changes in these sensitive variables may be more effectively achieved.

Another group in the model is disconnected variables; the ones with low influence and low dependence located near the axis's origin and their evolution seem to be rather excluded from the system. These variables are “access to the powerful team for research”, “wealth creation”, “research feasibility”, “using INEF facilities”, and “cooperation in problem-solving teams of enterprises”. These variables appear to be largely excluded from the core dynamics of the system. Their evolution and behavior seem relatively isolated from the primary factors driving the model's outcomes. It suggests that these disconnected variables may not be actively shaping or being shaped by the overarching system dynamics. Consequently, any efforts to directly target or manipulate these disconnected variables may limit the overall system performance.

The final group of variables are named secondary acting ones, located quite above the diagonal, which means they are more influential than dependent. These variables are: “experience”, “quality of education provided by elites”, and “education system satisfaction”. These variables occupy a position of relative importance within the system, while they may not be as directly dependent on the other variables. These secondary acting variables could be key leverage points for driving change or desired outcomes within the system. By targeting and manipulating these variables, it may be possible to indirectly affect the behavior and evolution of the system's more sensitive or disconnected elements.

Based on the findings of this paper, there are some suggestions for policymakers who work with elites, especially INEF and universities, to improve the elites’ influence on society (their effectiveness):

- Focus on enhancing the “elites' abilities” by designing better course syllabus at universities for students (potential elites), providing rigorous training programs, mentorship opportunities, and access to cutting-edge research tools and facilities.
- Implement financial support programs for elites, such as scholarships, grants, loans, work-study opportunities, and assistance with housing and other living expenses, to address their “financial problems”.
- Encourage and facilitate “doing research” by elites through dedicated research funding, infrastructure, and collaborative initiatives with industry and international partners. Also, incentives such as academic recognition, professional growth, grant opportunities, rewards for best researchers, and tax reliefs can be considered for researchers.
- Cultivate a strong sense of “national pride” among elites by highlighting their contributions to the country's scientific and technological advancements and fostering a patriotism and civic engagement culture.

 DOI: 10.22067/JSTINP.2024.87163.1095

- Actively work to improve the “place of the country in international rankings” by investing in research and development, promoting scientific excellence, and building global partnerships and collaborations.
- Monitor and address “education system satisfaction” by gathering feedback from students, faculty, and industry stakeholders and implementing data-driven improvements to the educational ecosystem.
- Leverage the “experience” of seasoned elites by creating mentorship programs, knowledge-sharing platforms, and opportunities for cross-generational collaboration with younger scholars and researchers.

The paper has been undertaken to structure the system influencing elites’ effectiveness in society. However, this work has answered some important questions and categorized the affecting variables; it highlighted several topics for further research:

One of the main findings of this paper is the high impact of social parameters on scientific elites’ effectiveness, which shows the importance of social studies in this subject. The most influential variable is social satisfaction; about 43% of the crucial variables are considered in this group. From the high influence variables in the subject, some suggestions for future research in social sciences are about designing different interventions to improve social satisfaction and national pride. Conducting in-depth studies on the underlying factors and drivers of social satisfaction and national pride among scientific elites could provide valuable insights for developing effective strategies. Also, studying the immigration tendency among scientific elites can help find solutions to decrease the brain drain and different social, economic, and cultural impacts of the problem. Examining the factors that influence the decision-making process of scientific elites when considering migration could inform policy interventions aimed at retaining top talent. Another research potential is developing scenarios for future interventions and simulating them to find the best strategy to improve elites’ effectiveness in society. Since the elites in medical sciences are not considered in the current paper, a more detailed study about this relatively large group of elites is suggested to future researchers. Expanding the scope of the analysis to include medical professionals could provide a more comprehensive understanding of the factors influencing the effectiveness of scientific elites across various disciplines. Since some variables in the model are categorized as disconnected, it may suggest that other unidentified variables or relationships are not being captured, which could be essential for a more comprehensive understanding of the system. Addressing these gaps could lead to a more robust and accurate representation of the complex dynamics. Further research to identify and integrate these missing elements could enhance the model's explanatory power and lead to more impactful interventions.

Acknowledgement

I am grateful to all of those with whom I have had the pleasure to work during the project in Iran National Elites Foundation (Yazd branch), especially Dr. Heidar Meftahizade

Disclosure statement

No potential conflict of interest was reported by the author(s).

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Journal of Systems Thinking in Practice
JSTINP, *QUARTERLY*
Homepage: jstinp.um.ac.ir
Online ISSN: 2821-1669, Print ISSN: 2980-9460
Research Article
DOI: 10.22067/JSTINP.2024.87456.1098
JSTINP 2024; Vol. 3, No. 4

A System Dynamics Model to Evaluate the LARG Supply Chain Elements in the Automotive Industry

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How to cite this article

Saberifard, N., Homayounfar, M., Fadaei, M., Taleghani, M., 2024. A system Dynamics Model to Evaluate the LARG Supply Chain Elements in the Automotive Industry. *Journal of Systems Thinking in Practice*, *3*(4), pp.102-131. doi: 10.22067/jstinp.2024.87456.1098.

URL: https://jstinp.um.ac.ir/article_45547.html.

ABSTRACT

The automotive industry is highly competitive, requiring robust supply chains to secure a strategic advantage. This study uses the Lean, Agile, Resilient, and Green (LARG) paradigms to evaluate supply chain performance in the automotive sector. This article developed a comprehensive system dynamics model to analyze these paradigms, incorporating key elements and their interactions within the supply chain. The model simulated eight scenarios to assess the impact of different strategies on supply chain performance. Research findings highlight that enhancing supply chain efficiency leads to the most significant increase in income, underscoring the importance of optimizing processes and reducing costs. Improving process flexibility emerged as the second most impactful strategy, enabling quicker adaptation to market changes and customer demands. Optimizing the flow of value and added value created also proved crucial, streamlining processes and reducing waste to enhance profitability. This research provides actionable insights for automotive industry stakeholders. Companies can substantially improve supply chain performance by focusing on efficiency, flexibility, and value flow. The study emphasizes the practical application of the LARG paradigms, offering a holistic framework for supply chain management in the automotive sector. In summary, the research system dynamics model demonstrates the critical role of LARG elements in driving supply chain success. This approach enables automotive companies to strategically enhance their supply chains, ensuring competitiveness in a dynamic market environment. The results offer valuable guidance for implementing effective supply chain strategies, paving the way for sustained profitability and growth.

Keywords

Supply chain; System dynamics, Automotive industry, LARG paradigms.

Article history

Received: 2024-04-01
Revised: 2024-07-23
Accepted: 2024-08-04
Published (Online): 2024-12-20

Number of Figures: 19 **Number of Tables: 4** **Number of Pages: 30** **Number of References:22**

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1. Introduction

The automotive industry requires robust supply chain strategies to cope with increasing complexity and market volatility. The Lean, Agile, Resilient, and Green (LARG) paradigms offer a comprehensive approach to enhancing supply chain performance by focusing on waste reduction, responsiveness, resilience, and sustainability (Akbarzadeh et al., 2019). The automotive industry is highly competitive and dynamic, requiring companies to continuously adapt and improve their supply chains to maintain a competitive edge (Divsalar et al., 2020). In this context, the role of supply chain management becomes critical (Rekabi et al., 2024). However, traditional, one-dimensional supply chain approaches are no longer sufficient to address the complexities and uncertainties of modern markets (Tavakol et al., 2023, Salahi et al., 2023). This research focuses on integrating the LARG paradigms into the automotive industry's supply chain,, particularly within the Iranian context. The LARG paradigm offers a comprehensive framework for enhancing supply chain performance (Jakhar et al., 2018). Lean principles aim to minimize waste and maximize value for customers; agile principles enhance the responsiveness to market changes (Saberifard et al., 2023); resilient principles improve the supply chain's ability to withstand disruptions (Kamali Chirani and Homayounfar, 2023), and green principles focus on environmental sustainability (Soufi et al., 2023). Integrating these paradigms can provide a holistic approach to managing supply chains in the automotive industry, ensuring efficiency, flexibility, robustness, and sustainability (Dubey et al., 2018).

Despite the theoretical advantages of the LARG paradigm, there is a lack of empirical studies evaluating its practical application and impact on the automotive industry's supply chain. This research addresses this gap by proposing a system dynamics model to evaluate the supply chain performance of SAIPA Automobile Company based on LARG principles.

Despite the theoretical benefits of the LARG paradigms, empirical evidence on their practical application and effectiveness in the automotive industry is limited (Homayunfar et al., 2018). This study aims to fill this gap by employing a system dynamics model to evaluate the supply chain of SAIPA Automobile Company. Through this approach, the study aims to provide actionable insights and strategies for improving supply chain performance, thereby contributing to the broader understanding of LARG paradigms in the automotive industry context. The automotive industry is a cornerstone of economic activity, characterized by intense competition and rapid change. Success in this industry hinges on maintaining a competitive supply chain (Lotfi et al., 2024). Traditional supply chain approaches often fail to address manufacturers' multifaceted challenges. This research aims to bridge this gap by applying the LARG paradigms to the supply chain of SAIPA Automobile Company. This study addresses how the LARG paradigms can be effectively integrated and evaluated within the automotive industry's supply chain. Specifically, this seeks to determine the most suitable scenarios for improving the supply chain performance of SAIPA Automobile Company through a system dynamics model.

Given the complexity and interdependencies within supply chains, a dynamic and holistic modeling approach is essential to capture the interactions and feedback loops among different elements. System dynamics modeling is particularly well-suited for this purpose as it simulates complex systems over time, providing insights into how various factors influence supply chain performance. The system dynamics model is employed in this study to evaluate the LARG supply chain elements because it enables the examination of dynamic behaviors and interrelationships within the supply chain. This approach allows us to simulate different scenarios and observe the long-term impacts of various strategies on supply chain performance. Using system dynamics, this study can develop and test dynamic hypotheses, visualize cause-and-effect relationships, and ultimately provide a robust framework for decision-making in supply chain management.

The remainder of the article is organized as follows. In the second section, a literature review of past research is presented. In the third section, the proposed framework of the problem is shown. The fourth section presents the results of applying the problem in the case study of SAIPA Automobile Company. Finally, in the fifth section, a general conclusion and suggestions for future research are presented.

2. Literature review

This section reviews the literature on the LARG supply chain paradigm and its application in various industries. For instance, Atefi et al. (2022) provided a dynamic model to measure the performance of a LARG supply chain with a balanced scorecard approach, using dynamic simulation to evaluate the performance. Atefi et al. (2021) also evaluated the LARG ness of a company's activities within a supply chain using a similar balanced scorecard and dynamic modeling approach. Sadeghi Moghadam et al. (2021) explored strategies to improve supply chain performance using LARG paradigms, highlighting strategies such as developing reverse logistics technology and creating electronic collaboration among supply chain members.

Izadyar et al. (2021) investigated the dynamic behavior of LARG supply chain management practices and their effect on sustainable performance in the automotive parts supply chain. They used fuzzy DEMATEL and fuzzy network analysis processes to prioritize practices and applied a system dynamics approach to evaluate sustainability performance. Shen et al. (2023)

 DOI: 10.22067/JSTINP.2024.87456.1098

examined green product supply chains under uncertainty with government intervention, using theoretical game models to derive equilibrium decisions for different planning scenarios.

Karmaker et al. (2023) studied the challenges of implementing Industry 5.0 amidst multiple supply chain disruptions due to the COVID-19 pandemic. They used qualitative and quantitative methods to prioritize these challenges and analyze their interrelationships. Vergara et al. (2023) measured performance in resilient-sustainable supply chains using fuzzy multi-criteria techniques, focusing on the characteristics and influencing relationships within sustainable-resilient supply chains. Using structural equation modeling, Uddin (2022) explored the interactions between strategic alliances, supply chain cooperation, operational performance, and innovation performance.

Recent studies have also contributed significantly to the understanding of LARG supply chains. For example, a study titled "A System Dynamics Model of the LARG Supply Chain Diffusion in the Steel Industry of Yazd" developed a model to understand the diffusion process of LARG supply chain practices in the steel industry. Another study, "Developing the LARG-Effective Supply Chain Model Using a System Dynamics Approach," proposed a comprehensive model to evaluate the effectiveness of LARG supply chain practices. Additionally, Sonar et al. (2022) investigated the role of the LARGS (Lean, Agile, Resilient, Green, and Sustainable) paradigm in supplier selection, identifying important criteria and developing a hierarchical relationship among these criteria. Significant advancements have been made in LARG supply chain management in recent years. For instance, Atefi et al. (2022) and Atefi et al. (2021) utilized dynamic simulation and balanced scorecard approaches to evaluate LARG supply chain performance. Sadeghi Moghadam et al. (2021) proposed strategies for improving supply chain performance using LARG paradigms. Izadyar et al. (2020) investigated the sustainable performance of LARG supply chain management practices using fuzzy DEMATEL and network analysis processes, followed by a system dynamics evaluation.

Shen et al. (2023) examined green product supply chains under uncertainty, considering government intervention and using theoretical game models. Karmaker et al. (2023) analyzed the challenges of implementing Industry 5.0 amidst supply chain disruptions due to the COVID-19 pandemic, employing qualitative and quantitative methods. Vergara et al. (2023) focused on resilient-sustainable supply chains, utilizing fuzzy multi-criteria techniques to determine key characteristics and relationships. Using structural equation modeling, Uddin (2022) studied the impact of strategic alliances and supply chain cooperation on operational and innovation performance. To better illustrate the unique aspects of our study and how it differs from related works, Table 1 presents each study's key differences and contributions.

Table 30. Some related research

Study	Focus	Methodology	Key Findings	Contribution
Atefi et al. (2022)	LARG performance measurement	Dynamic simulation, balanced scorecard	Strategy map, indicators for LARG	Performance evaluation framework using dynamic simulation
Atefi et al. (2021)	LARG ness evaluation	Dynamic modeling, balanced scorecard	Integration of LARG and balanced scorecard	Evaluation of company's performance using LARG indicators
Sadeghi Moghadam et al. (2021)	LARG improvement strategies	Case study	Reverse logistics, closed-loop supply chain, electronic collaboration	Identification of effective strategies for LARG improvement
Izadyar et al. (2021)	Sustainable performance of LARG	Fuzzy DEMATEL, system dynamics	Prioritization of LARG practices	Sustainability performance evaluation of LARG practices
Shen et al. (2023)	Green supply chain under uncertainty	Theoretical game models	Government intervention effects	Decision-making framework for green supply chains
Karmaker et al. (2023)	Industry 5.0 and supply chain disruptions	Qualitative and quantitative methods	Challenges of Industry 5.0	Prioritization and analysis of implementation challenges
Our Study	LARG supply chain evaluation in automotive industry	System dynamics model	Long-term impact of LARG strategies on supply chain performance	Holistic evaluation framework for automotive supply chains

A review of the existing literature reveals a gap in empirical studies evaluating the practical application of LARG paradigms in the automotive industry's supply chain. While previous research has explored dynamic models and performance evaluation techniques, this study uniquely focuses on applying a system dynamics model to the LARG supply chain of SAIPA Automobile Company. By integrating LARG principles, we aim to provide a holistic evaluation framework that addresses efficiency, flexibility, resilience, and sustainability. This study advances the field by providing a comprehensive system dynamics model that evaluates the LARG supply chain elements in the automotive industry. This research offers new insights into the long-term impacts of various strategies on supply chain performance, thereby contributing to a deeper understanding of how LARG paradigms can be practically applied and measured in real-world scenarios. This study uniquely integrates LARG principles into a system dynamics model tailored to the automotive industry. Unlike previous studies focusing on individual elements or theoretical models, our research provides a comprehensive, empirical evaluation of LARG supply chain elements, offering actionable insights for improving supply chain performance in real-world scenarios. This study makes several incremental contributions to the existing body of knowledge in LARG supply chain evaluation. Firstly, this study provides a practical application of the LARG paradigms within the automotive industry, specifically focusing on the supply chain of SAIPA Automobile Company. Secondly, by employing a system dynamics model, we offer a robust framework for simulating and evaluating the long-term impacts of various LARG strategies on supply chain performance.

- This study provides empirical evidence on the effectiveness of integrating LARG principles in the automotive supply chain, highlighting the benefits of a holistic approach to supply chain management.
- This study introduces a novel system dynamics model that can simulate different scenarios and strategies, offering valuable insights for decision-makers in the automotive industry.
- This study's findings contribute to a deeper understanding of how LARG paradigms can be practically applied and measured, advancing the field of supply chain management by bridging the gap between theoretical concepts and real-world applications.

By addressing these aspects, our study not only fills existing gaps in the literature but also provides a comprehensive tool for practitioners to enhance supply chain performance by integrating LARG principles.

3. Methodology

System dynamics is an approach derived from computer basics used to analyze and solve complex problems, emphasizingpolicy analysis and design. Simulation using system dynamics models is very beneficial for learning the complexities of system dynamics. This attitude is a very valuable tool for identifying effective policies in existing systems and improving system behavior by using changes in its parameters and structural changes. This approach is an object-oriented simulation method based on feedback relationships, which, in addition to creating the participation of users of each model in its development, creates significant simplicity and speed in system definition and model development. One of the capabilities of this approach is the group development of models and the simplicity of model modification in response to system changes. The steps of the system dynamics method are:

- Problem statement
- Development of dynamic hypothesis
- Development of a simulation model
- Model testing
- Design and evaluation of policies

The system dynamics approach seeks to identify feedback closed loops to check the system's functioning. A feedback loop includes a closed chain of causal relationships affecting the primary variable in selection. Feedback loops include a positive feedback loop, also called a reinforcement loop. It also consists of negative feedback loops or, in other words, a balancing loop. These loops are loops in which if a component changes in one direction, it reinforces the loop of changes in the corresponding direction. Therefore, it can be acknowledged that the negative feedback loop is a loop in which if a component is changed in one direction, the desired loop will oppose the changes of that component in that direction. In short, it can be said that the negative loop has a neutralizing role and is against change. In the following, according to the identification of concepts and categories resulting from in-depth interviews with experts, according to the LARG supply chain paradigms, four causal loops were identified, according to which four dynamic hypotheses were presented.

- Lean Supply Chain Paradigm: Increasing the quality of products and services and improving quality control and supervision will lead to better customer support, enhanced coordination, reduced operating costs, increased profitability, competitive advantage, and overall supply chain efficiency.
- Agile Supply Chain Paradigm: Strengthening expertise and management skills, improving cooperation with suppliers, and enhancing risk management will increase organizational capability, innovation, and market responsiveness.
- Resilient Supply Chain Paradigm: Improving process flexibility and human resources management will improve production planning, inventory control, and logistics, enhancing supply chain resilience.
- Green Supply Chain Paradigm: Emphasizing legal requirements, social responsibility, and green practices will lead to optimized warehousing, production, and effective waste management, ultimately improving environmental sustainability and green marketing.

These hypotheses are directly linked to the research objectives of evaluating the impact of LARG paradigms on the supply chain performance of SAIPA Automobile Company. This article aims to identify effective strategies for enhancing supply chain efficiency, flexibility, resilience, and sustainability by testing these hypotheses through system dynamics modeling.

3.1. Validation of dynamics model

Validation of the model in this study is tested by matching the model's behavior with the real behavior. First, the historical data is drawn graphically, and the behavior of the model is compared. The question that needs to be answered in this regard is whether the model reproduces the model's behavior?. It means that the model's behavior can be matched with historical data. Can the simulated structure show the system's behavior in the real world? If the model can show the real world and match the historical data, it can be claimed that the model is validated. Validation in system dynamics models is divided into two types: structural validation and behavioral validation. Structural validation means creating relationships in the model that clearly and adequately represent the relationships of the real world (considering the study's purpose). Behavioral validation means that the model's behavior sufficiently represents the phenomenon's behavior in the real world. There will be no behavioral validation unless the model has adequate structural validation.

4. Findings

This section uses the system dynamics approach to address the hybrid modeling of the large supply chain in the automotive industry. The following identifies the components of the LARG supply chain paradigms for modeling. System dynamics is an approach derived from computer basics used to analyze and solve complex problems, emphasizing policy analysis and design. Simulation using system dynamics models is very beneficial for learning the complexities of system dynamics. This attitude is a very valuable tool for identifying effective policies in existing systems and improving system behavior by using changes in its parameters and structural changes. This approach is an object-oriented simulation method based on feedback relationships, which, in addition to creating the participation of users of each model in its development, creates significant simplicity and speed in system definition and model development. One of the capabilities of this approach is the group development of models and the simplicity of model modification in response to system changes.

The selection of variables and parameters was guided by their relevance to the automotive industry's supply chain and their impact on the LARG paradigms. The criteria included:

(13) **Relevance to Supply Chain Performance:** Variables were selected based on their direct impact on supply chain efficiency, flexibility, resilience, and sustainability. For example, product quality, process flexibility, and green production practices are critical for maintaining competitiveness in the automotive industry.

- **Data Availability:** Variables for obtaining reliable data were prioritized. Historical data from SAIPA Automobile Company and industry reports were used to validate the model.
- **Expert Input:** Industry experts provided insights into the most significant factors affecting the automotive supply chain. Their input was crucial in identifying resource utilization, network structure, and supplier cooperation variables.
- **System Dynamics Principles:** The selection of variables was also guided by system dynamics principles, focusing on feedback loops and causal relationships that drive system behavior.

The relevant paradigms and their variables are listed in Table 2.

Table 31. LARG supply chain paradigms for system dynamics modelling

Components of identified loops of lean paradigm	Components of the identified loops of agile paradigm
Quality of products and services	Strengthening the organization's capability
Quality control and monitoring	Risk management
Using a network structure	Uncertainty
Communication and interaction with stakeholders	Expertise and management skills
Coordination	Speed
Information and communications technology	Synergy
Financial planning and working capital management	Budgeting
Sharing information and knowledge	Responding to market needs
Attention to the flow of value and added value created	Development and focus on market
Customer support	Commitment
Operating costs	Innovation
profitability	Cooperation with suppliers
Supply chain efficiency	---------
Competitive advantage	---------
Utilization and optimal use of resources	---------
Components of identified loops of resilient paradigm	Components of identified loops of green paradigm
Process flexibility	Green production and operations
Human resources management	Choosing a green supplier
Contradiction, disruption, and conflict in the chain	Legal requirements, regulations, and standards
Logistics	Responsiveness to partners
Sourcing	Social responsibility
Integrity	Management of energy consumption and resources
Strategic alliance	Optimal warehouse management
Production planning and inventory control	Waste management
---------	Performance and monitoring factors
---------	Green marketing

As it is clear, investigating the model in the field of system dynamics consists of four steps, each of which is discussed below.

4.1. Definition of dynamic problem

As mentioned above, using a supply chain paradigm cannot create maximum efficiency for this chain, and each paradigm ignores some of the important indicators in the supply chain according to its strengths. Therefore, in establishing a LARG supply chain, in addition to making the most of the advantages of each of the four paradigms, it also covers the weaknesses of each of them, which is considered the most important factor in the dynamic problem.

4.2. Drawing causal diagrams and dynamic hypotheses

The system dynamics approach seeks to identify feedback closed loops to check the system's functioning. A feedback loop includes a closed chain of causal relationships affecting the primary variable in selection. Feedback loops include a positive feedback loop, also called a reinforcement loop. It also consists of negative feedback loops or, in other words, a balancing loop. These loops are loops in which if a component changes in one direction, it reinforces the loop of changes in the corresponding direction. Therefore, it can be acknowledged that the negative feedback loop is a loop in which if a component is changed in one direction, the desired loop will oppose the changes of that component in that direction. In short, it can be said that the negative loop has a neutralizing role and is against change. In the following, according to the identification of concepts and categories resulting from in-depth interviews with experts, according to the LARG supply chain paradigms, four causal loops were identified, according to which four dynamic hypotheses were presented.

4.2.1. The first dynamic hypotheses (presenting the circular causal model of the lean supply chain paradigm)

According to the identified factors, the attention of automobile companies to increase the quality of products and services and quality control and supervision makes them provide proper support to customers and thus take into account their needs and demands. On the other hand, by emphasizing information and communication technology, automobile companies can speed up communication and interaction with stakeholders, strengthening the process of sharing knowledge and information. The sum of these factors can increase coordination between them; meanwhile, using a network structure can also strengthen coordination. On the other hand, using a network structure helps automobile companies in financial planning, working capital management, and the use and optimal use of resources. With this support, financial planning and working capital management and the employment and optimal use of resources can significantly help to reduce operating costs, increase profitability, and improve the competitive advantage and efficiency of the supply chain; all these factors can help strengthen the value flow and strengthen the added value of the supply chain. Figure 1 illustrates the circular causal model of the lean supply chain paradigm.

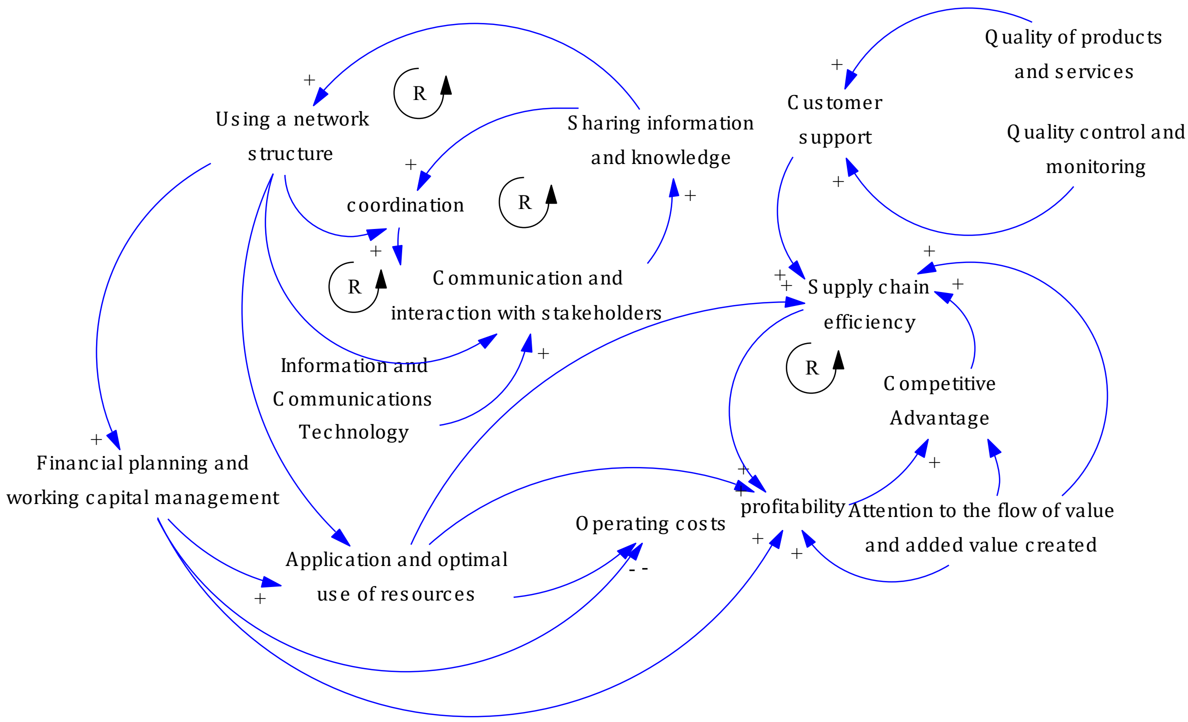

Figure 53. Presenting the circular causal model of the lean supply chain paradigm

4.2.2. The second dynamic hypotheses (presenting the circular causal model of the agile supply chain paradigm)

The expertise and management skills of automotive companies can provide special help to proper and long-term cooperation with suppliers, more appropriate risk management, strengthening the organization's capabilities, innovation, and appropriate budgeting. In this regard, strengthening the organization's appropriate budgeting can help strengthen its capabilities. Also, expertise and skills in management and synergy can help innovation in the organization, and in this way, the response to market needs can be strengthened. In the inter-model loop, speed affects synergy, and synergy affects commitment, and again, in the return loop, commitment affects speed, and this loop can continue incrementally. On the other hand, cooperation with suppliers can help to strengthen risk management, which reduces uncertainty. In the return loop, reducing uncertainty helps to strengthen risk management. In one of the loops, the development and focus on the market affects responding to market needs and strengthening the capacity of the organization's capabilities and strengthens them. Figure 2 displays the circular causal model of the agile supply chain.

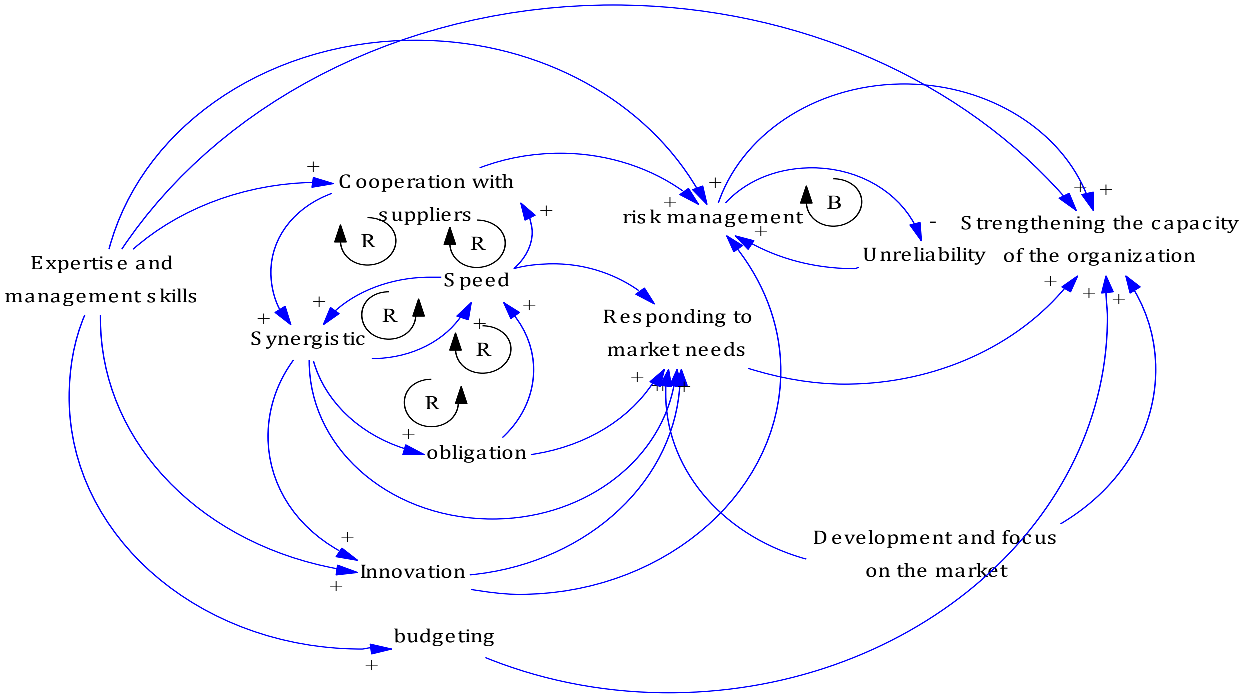

Figure 54. Presenting the circular causal model of the agile supply chain paradigm

4.2.3. The third dynamic hypotheses (presenting the circular causal model of the resilient supply chain paradigm)

The presence of skilled and expert human resources and their management in automotive companies can help the process flexibility of these companies. In this regard, the existence of expertise in human resources, along with process flexibility, can increase and improve the effectiveness of production planning and inventory control. On the other hand, process flexibility reduces conflict, disruption, and conflict in the supply chain and reduces them. In the other loop, production planning and inventory control strengthen process flexibility, and in the return loop, strengthening process flexibility leads to strengthening production planning and inventory control. Also, in one of the loops, process flexibility affects strengthening the logistics, and in the return loop, strengthening the logistics leads to strengthening of process flexibility. In one of the model loops, logistics leads to the strengthening of the strategic alliance, strategic alliance also strengthens integration, and in the next step, integration helps to strengthen sourcing, and finally, sourcing helps to strengthen logistics. In one of the loops of the model, integration leads to the development of sourcing, and the development and strengthening of sourcing leads to the development of integration. Figure 3 shows the circular causal model of the resilient supply chain paradigm.

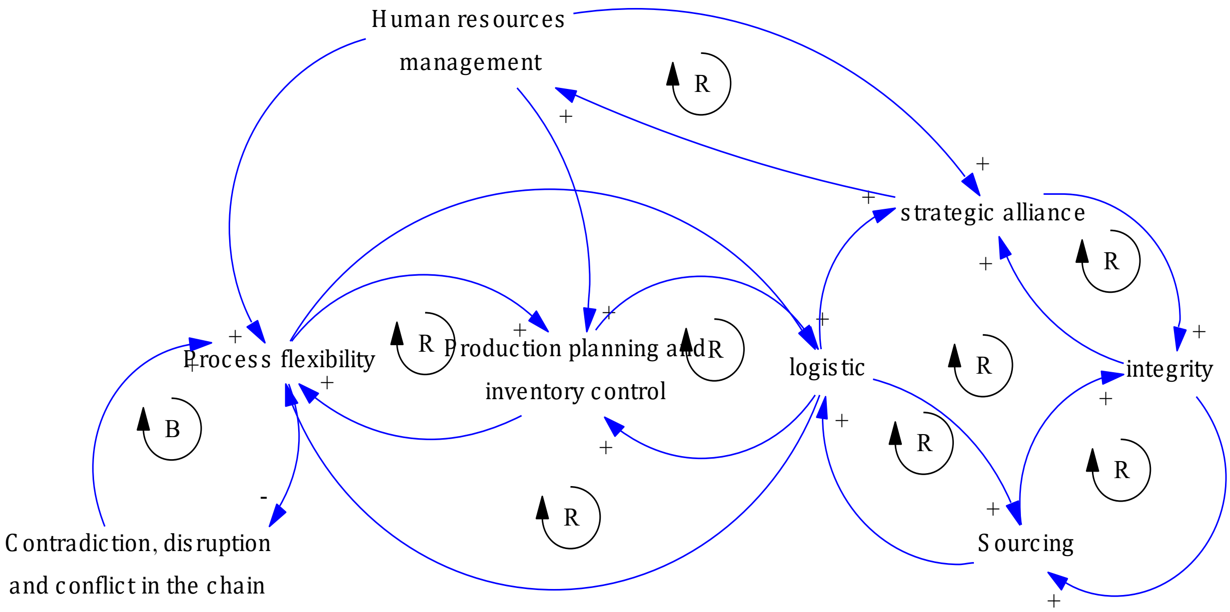

Figure 55. Presenting the circular causal model of the resilient supply chain paradigm

4.2.4. The fourth dynamic hypotheses (presenting the circular causal model of the green supply chain paradigm)

Emphasizing the legal requirements, regulations, and standards in automobile manufacturing can cause these companies to move towards more social responsibility, and increasing the attention of automobile manufacturing companies to social responsibility can help to choose green suppliers and require the company to choose suppliers that have the most indicators of greenness and also increase the company's responsiveness to its partners. Providing raw materials for automotive companies from suppliers can also optimize warehousing and prevent overstocking of raw materials, which can significantly help the establishment of green warehousing in automotive companies. Considering the conditions of green warehousing in the automotive industry and having raw materials with the least negative effects of pollution, the company's research and development process designs products. It provides samples in the form of pilot production for the production process. After investigating the performance indicators, the products are produced with maximum green indicators. In case of defects in production, corrective measures will be developed to fix them, and in this case, green production and operations in the company will be in the most optimal possible state. The attention of automotive companies in green production to reduce environmental pollution and pollutants and their efforts to reduce the effects of pollution lead to the management of energy consumption and resources in automobile manufacturing. Since the negative aspects of pollution in products are considered in green production, this factor can strengthen the company's ability to manage waste. Therefore, the production cycle is improved by identifying the weaknesses in the production line and reducing waste, as well as the policies of reducing production line waste and recycling waste. The product life is increased, which can encourage and motivate green consumers to use the company's products and services. In this way, the green marketing of automotive companies will be developed. It should be noted that the performance and regulatory factors of automotive companies should pay special attention to all these factors continuously. Figure 4 depicts the circular causal model of the green supply chain paradigm.

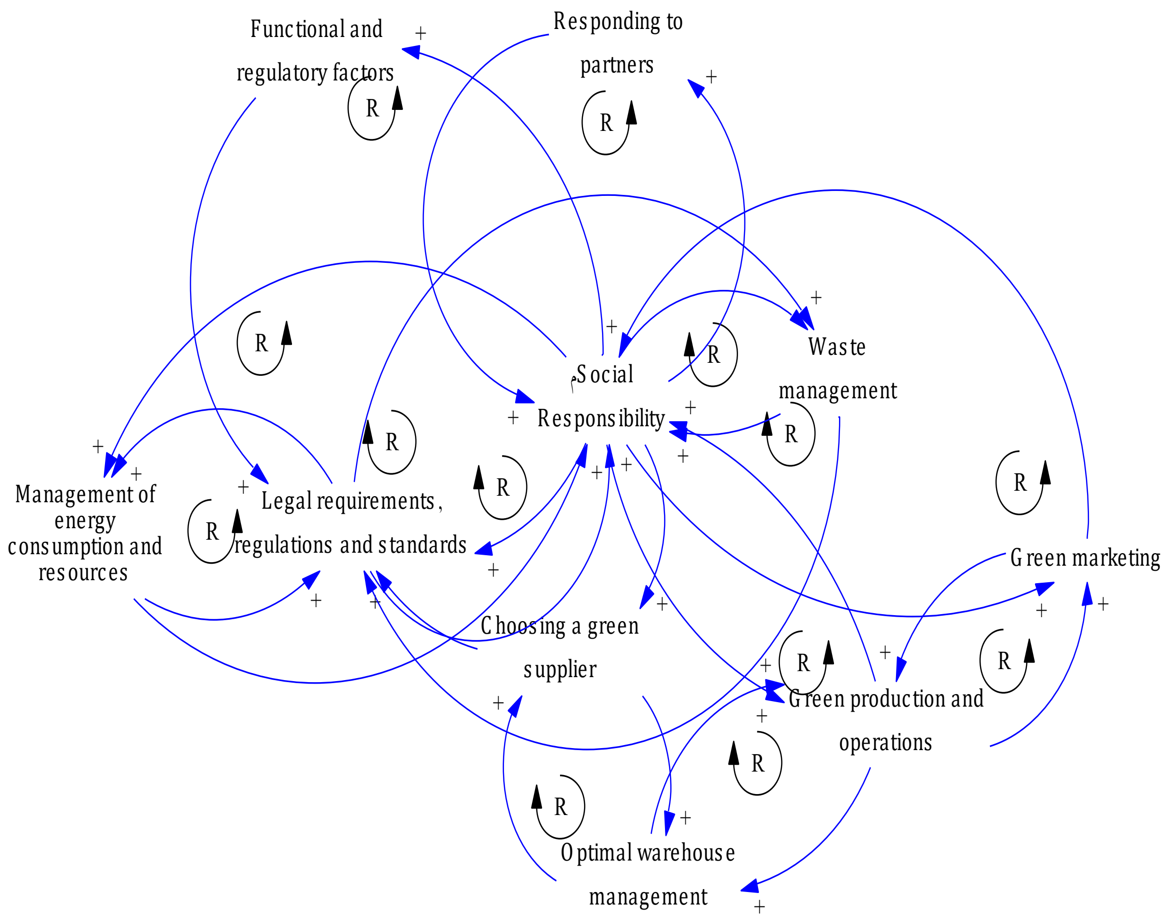

Figure 56. Presenting the circular causal model of the green supply chain paradigm

Finally, by identifying the circular causal model of the lean, agile, resilient, and green supply chain paradigm, the cause and effect and flow diagram based on the LARG supply chain are shown in Figure 5.

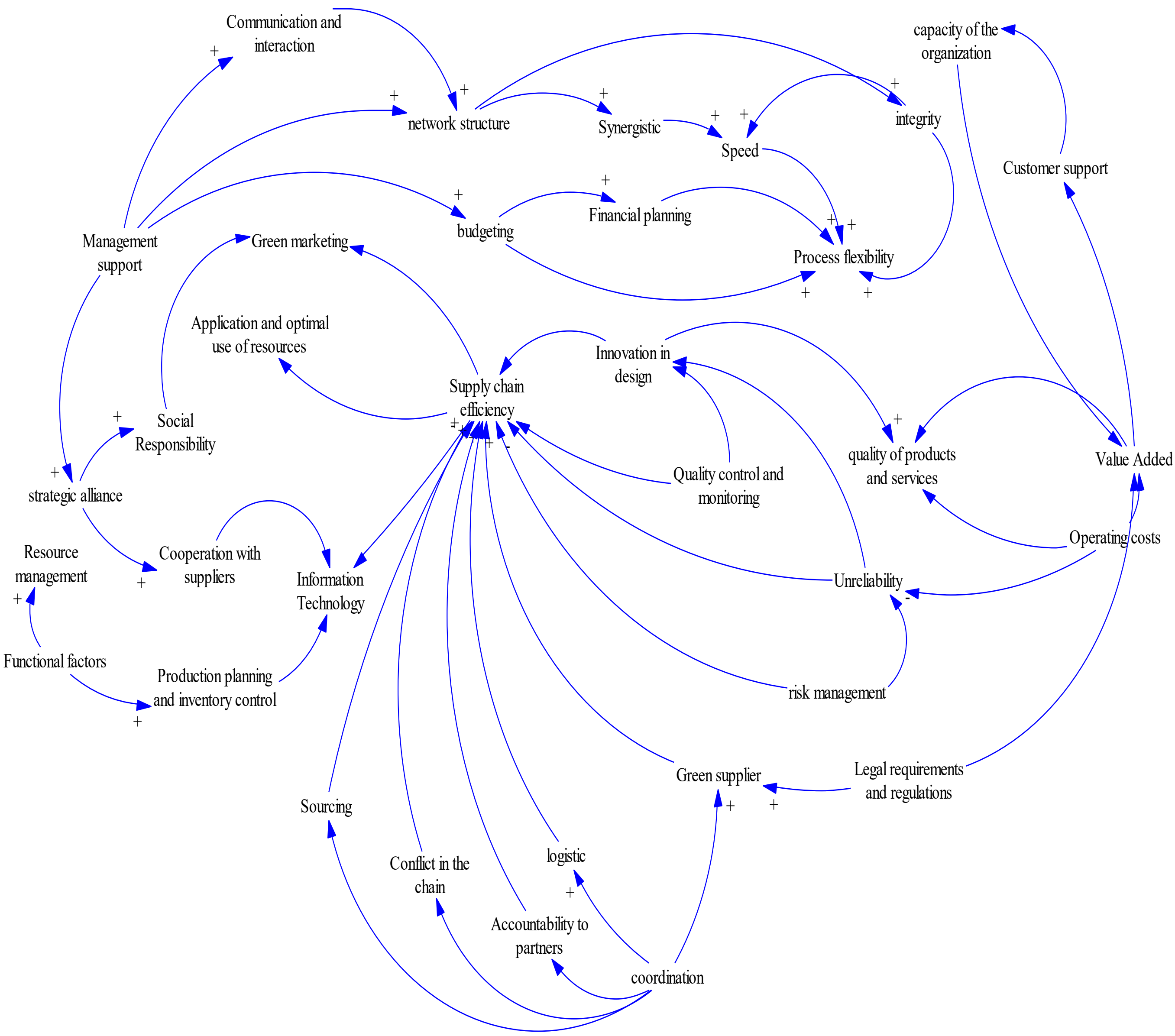

Figure 57. Cause and effect and LARG flow diagram

4.3. Drawing stock and flow diagrams

In this part of the research, the modeling of inventory-flow diagrams is shown in Figure 6. For the final modeling, Stock, flow, and auxiliary variables need to be identified, which are introduced in this section.

The system dynamics approach seeks to identify feedback closed loops to check the system's functioning. A feedback loop includes a closed chain of causal relationships affecting the primary variable in selection. Feedback loops include a positive feedback loop, also called a reinforcement loop. It also consists of negative feedback loops or, in other words, a balancing loop. These loops are loops in which if a component changes in one direction, it reinforces the loop of changes in the corresponding direction. Therefore, it can be acknowledged that the negative feedback loop is a loop in which if a component is changed in one direction, the desired loop will oppose the changes of that component in that direction. In short, it can be said that the negative loop has a neutralizing role and is against change. In the following, according to the identification of concepts and categories resulting from in-depth interviews with experts, according to the LARG supply chain paradigms, four causal loops were identified, according to which four dynamic hypotheses were presented:

1. Lean Supply Chain Paradigm
   - Positive Feedback Loop: Increasing product and service quality → Better customer support → Enhanced coordination → Reduced operating costs → Increased profitability → Competitive advantage → Improved supply chain efficiency.
   - Negative Feedback Loop: Improved quality control and monitoring → Reduction in operational defects → Lower operational costs → Increased profitability.
2. Agile Supply Chain Paradigm
   - Positive Feedback Loop: Strengthening management skills → Better supplier cooperation → Improved risk management → Enhanced organizational capability → Increased innovation → Better market responsiveness.
   - Negative Feedback Loop: Improved risk management → Reduced uncertainty → Enhanced stability in operations.
3. Resilient Supply Chain Paradigm
   - Positive Feedback Loop: Improved process flexibility → Better production planning and inventory control → Enhanced logistics → Strengthened strategic alliances → Improved sourcing → Enhanced resilience.
   - Negative Feedback Loop: Better management of disruptions → Reduced conflicts and inefficiencies → Enhanced process stability.
4. Green Supply Chain Paradigm
   - Positive Feedback Loop: Emphasis on legal requirements and social responsibility → Choosing green suppliers → Optimized warehousing → Improved green production and operations → Effective waste management → Better green marketing.
   - Negative Feedback Loop: Improved waste management → Reduction in environmental impact → Enhanced sustainability.

It should be noted that from the modeling of the four paradigms, the mathematical equations introduced in Table 3 were extracted for the final analysis.

Table 32. Introduction of the problem variables and their operational definition

No.	Variable	Type	Mathematical relation
1	Attention to quality of products and services	Auxiliary	0.1(f5(Green Design)
2	Attention to quality control and monitoring	Auxiliary	IF THEN ELSE (human resource=>0.1,0.4, IF THEN ELSE (human resource-es =>0.09,0,0.2))
3	Using a network structure	Auxiliary	RAMP (Green Product Quality,1,9) -((0.2*Government support) +Orders for green products-green production)
4	Communication and interaction with stakeholders	Auxiliary	Skilled human resources/30
5	Coordination	Auxiliary	SMOOTH (human resources*0.2,1)
6	Information and communications technology	Auxiliary	F3(training)
7	Financial planning and working capital management	Auxiliary	(STEP (Green recovery,2) +Managers Support+(2*Media support))
8	Sharing information and knowledge	Auxiliary	(SMOOTH (Change in the rate of orders, 10))
9	Attention to flow of value and added value created	Auxiliary	F1(Media support)
10	Customer support	Auxiliary	SMOOTH (0.3,1)
11	Operating costs	Auxiliary	SMOOTH (human resources,2)
12	Profitability	Flow	STEP (0.5, Government support) +(1/Green Product Price)
13	Supply chain efficiency	Auxiliary	0.59
14	Competitive advantage	Stock	(STEP (Green recovery,2) +Managers Support+(2*Media support))
15	Utilization and optimal use of resources	Auxiliary	(SMOOTH (Change in the rate of orders, 10))
16	Strengthening the capacity of the organization	Auxiliary	F1(Media support)
17	Risk management	Auxiliary	Skilled human resources/30
18	Uncertainty	Auxiliary	SMOOTH (human resources*0.2,1)
19	Expertise and management skills	Flow	0.4/Skilled human resource
20	Speed	Auxiliary	(STEP (Green recovery,2) +Managers Support+(2*Media support))
21	synergy	Auxiliary	(SMOOTH (Change in the rate of orders, 10))
22	Budgeting	Auxiliary	F1(Media support)
23	Responding to market needs	Flow	(STEP (Green recovery,2) +Managers Support+(2*Media support))
24	Development and focus on market	State	(SMOOTH (Change in the rate of orders, 10))
25	Management commitment and support	Auxiliary	F1(Media support)
26	Innovation in design	Auxiliary	F4(Supervision over implementation of Laws and regulations)
27	Cooperation with suppliers	Auxiliary	(STEP (Green recovery,2) +Managers Support+(2*Media support))
28	Process flexibility	Auxiliary	(SMOOTH (Change in the rate of orders, 10))
29	Human resources management	Flow	SMOOTH (human resources,2)
30	Contradiction, disruption, and conflict in the chain	Auxiliary	SMOOTH (human resources,2)
31	Logistics	Auxiliary	IF THEN ELSE (Green fuel>=0.9, SMOOTH (0.8,2), f2(Green fuel))
32	Sourcing	Auxiliary	RAMP (Green Product Quality,1,9) -((0.2*Government support) +Orders for green products-green production)
33	Integrity	Auxiliary	SMOOTH (human resources,2)
34	Strategic alliance	Auxiliary	RAMP (0.09, 0, 10)
35	Production planning and inventory control	Auxiliary	(0.3+(f4(Supervision over implementation of Laws and regulations))

No.	Variable	Type	Mathematical relation
36	Green production and operations	Flow	((0.2*Green Design) +(0.1*Green Suppliers) +(0.2*Technology) +(0.2*Order for green products) +(0.15*Skilled Human Resources) +(0.3Supervision over implementation of Laws and regulations))
37	Choosing a green supplier	Auxiliary	(0.2+(0.7* Supervision over implementation of Laws and regulations))
38	Legal requirements, regulations, and standards	Auxiliary	(0.3+PULSE TRAIN (1, Government support,9,9)
39	Responsiveness to partners	Auxiliary	0.3+RAMP (Managers support, 1,9)
40	Social responsibility	Auxiliary	Employment-HR Quit Rate-Skill enhancement
41	Management of energy consumption and resources	Auxiliary	0.3+f4(Supervision over implementation of Laws and regulations)
42	Optimal warehouse management	Stock	(Green production)-(sales)
43	Waste management	Flow	0.1+(0.3*Government support) +(0.5* Supervision over implementation of Laws and regulations)
44	Performance and monitoring factors	Auxiliary	(0.2) +SMOOTH (Rule, 2)
45	Green marketing	Auxiliary	Employment-HR Quit Rate-Skill enhancement
46	Recruiting expert staff by other companies	Flow	IF THEN ELSE (human resource>=0.1,0.4, IF THEN ELSE (human resource-es>=0.09,0,0.2))
47	Extreme price fluctuation	Flow	RAMP (Green Product Quality,1,9) -((0.2*Government support) +Orders for green products-green production)
48	Retirement rate of professionals	Flow	Skilled human resources/30
49	Dismissal rate	Flow	SMOOTH (human resources*0.2,1)
50	Skilled workforce	State	(Skill Enhancement-Job quit rate-retirement rate)
51	Human resources	State	Employment-HR Quit Rate-Skill enhancement
52	Income	State	Sales

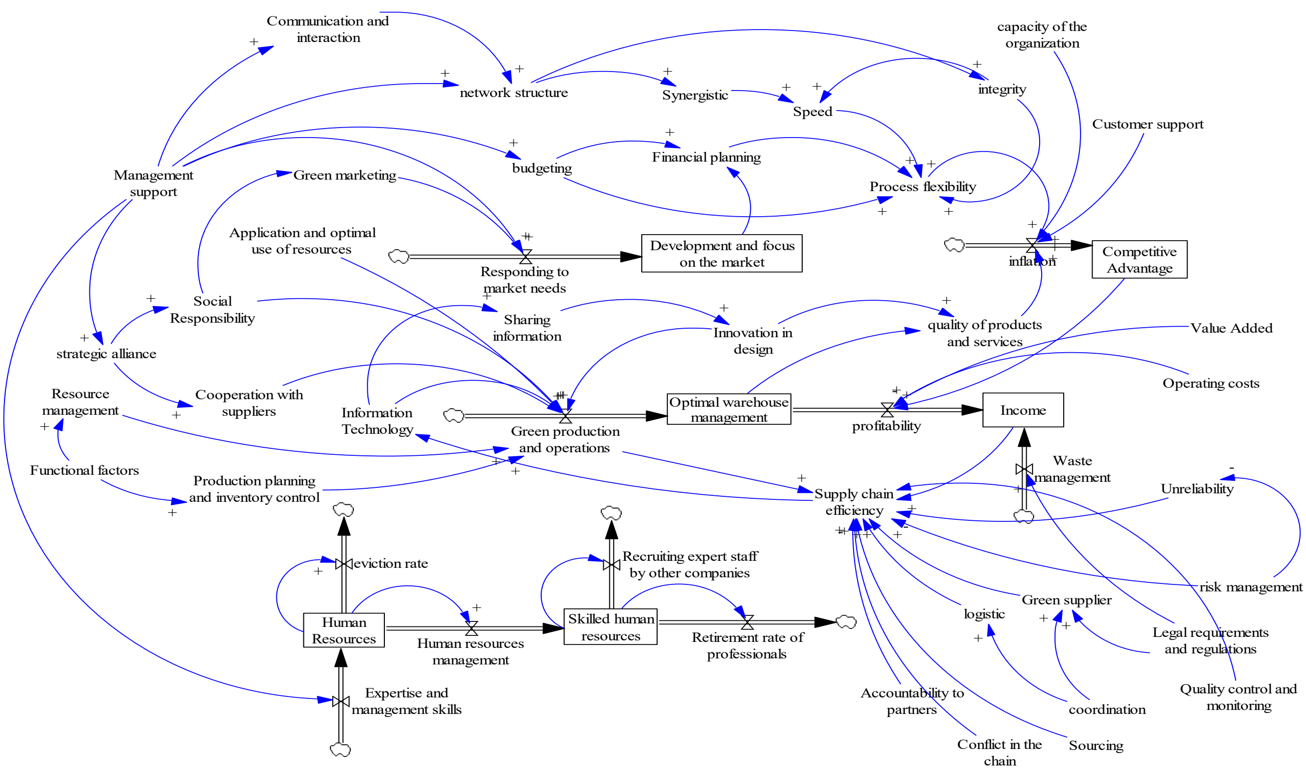

Figure 58. LARG supply chain model for automobile companies

According to the definition of state variables in the simulation model and the initial value surveyed by the experts, the level of competitiveness according to the effective factors is increasing over time, indicating the logical behavior of the model. Figure 7 shows changes in competitiveness in the simulation of competitive advantage in 100 months. Moreover, Figure 8 displays that according to the initial number of surveys by the experts, the level of development and focus on the market is increasing over time, showing the logical behavior of the model.

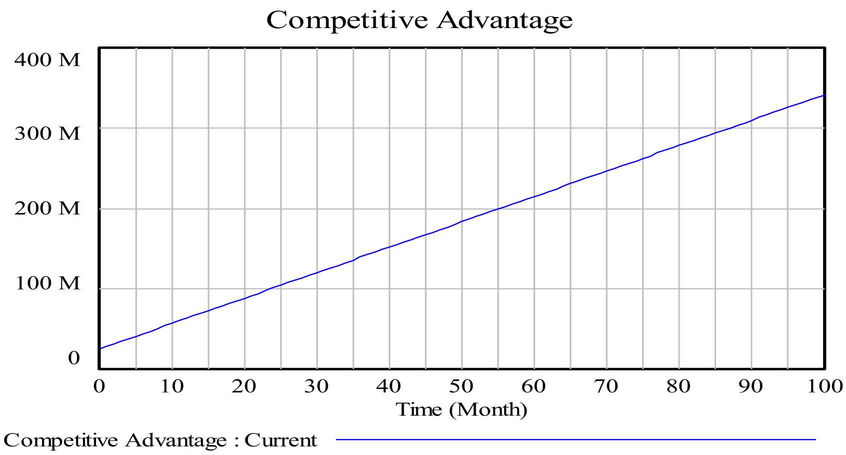

Figure 59. Simulation of competitive advantage over time

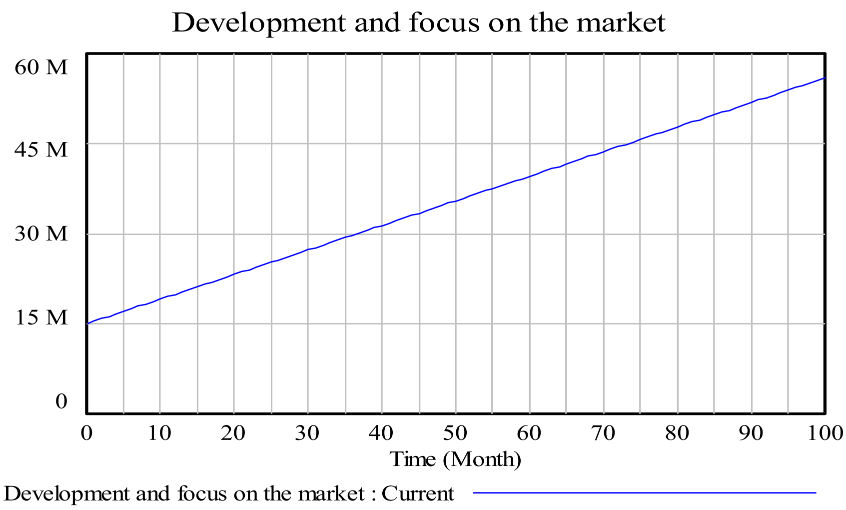

Figure 60. Simulation of development and focus on market over time

Model validation is one of the most important stages of modeling. Since the system dynamics model usually represents the real operation of real systems in some aspects, it is necessary and important for the model to be close to the real world to verify the model. In order to validate, the behavior of the model was examined, and some model variables were subjected to abrupt changes and boundary conditions. As seen in Figure 9, the income decreased significantly with

 DOI: 10.22067/JSTINP.2024.87456.1098

the decrease in customer orders delivered. On the other hand, with the increase in the delivery of customer orders, the income increased.

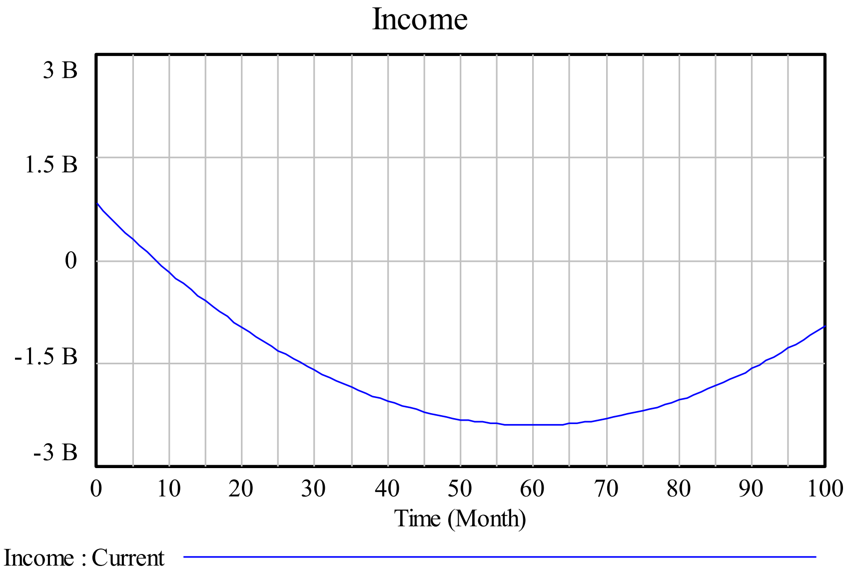

Figure 61. Boundary test related to the number of customer order deliveries according to income

In addition to the boundary test, a test to reproduce the participants' behavior was considered. In this case, the simulated behavior for the model is reproduced to be compared with the real data. Figure 10 illustrates that according to the initial value surveyed by experts, experts' retirement rate is increasing over time, showing the logical behavior of the model.

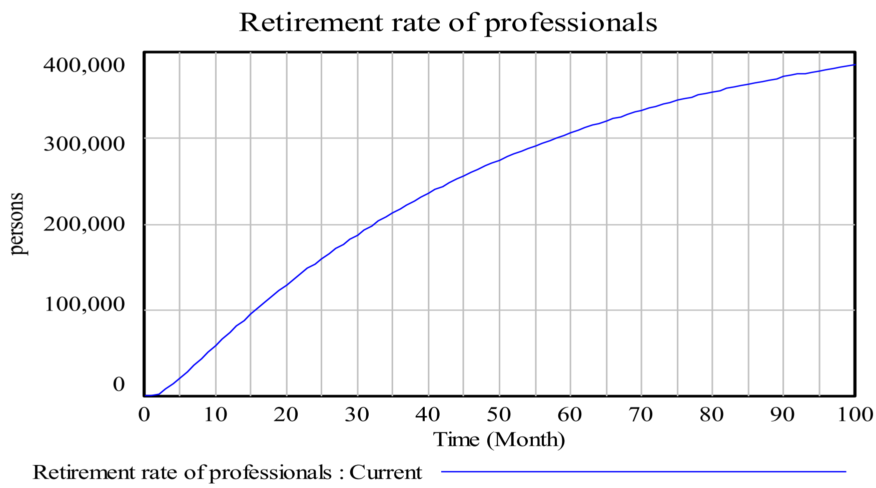

Figure 62. Graph of the retirement rate of experts over time

Figure 11 depicts that according to the initial value surveyed by the experts, the level of human resource management according to the effective factors increased up to one-fifth of the simulation period and then remained constant until the end of the predicted period, indicating the logical behavior of the model.

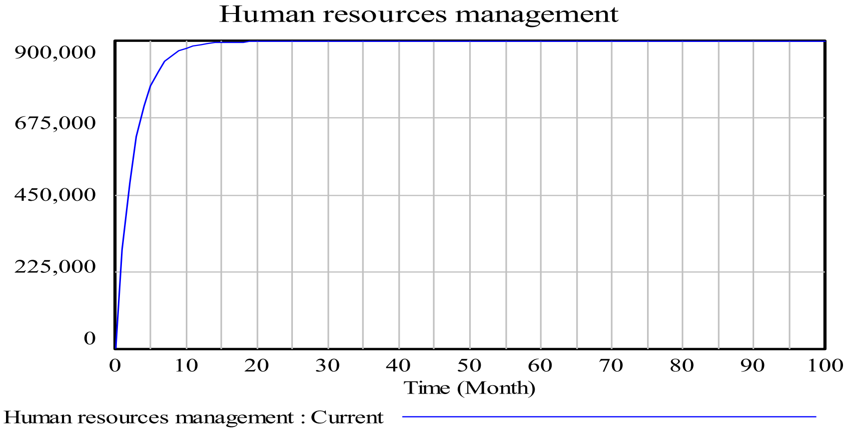

Figure 63. Graph of human resource management over time

Validation of the model in this study is tested by matching the model's behavior with real behavior. First, historical data is drawn graphically, and the model's behavior is compared. The question that needs to be answered in this regard is whether the model reproduces the behavior of the real system. The model's behavior can be matched with the historical data. If the model can show the real world and match the historical data, it can be claimed that the model is validated. Validation in system dynamics models is divided into two types: structural validation and behavioral validation.

Boundary Adequacy Test: Ensures that the model includes all relevant variables and excludes irrelevant ones. The boundary adequacy test confirms that the selected variables and parameters sufficiently capture the system dynamics of the automotive supply chain.

Boundary Condition Test: The boundary condition test ensures the model performs correctly under extreme conditions. This test involves setting model variables to extreme values and observing the system's response. For example, reducing the number of customer order deliveries to zero should significantly decrease income, which is validated by the model's behavior (Figure 9).

Integrity Error Test: Ensures no logical or computational errors in the model. This test involves checking the consistency and accuracy of the model equations and their implementation.

Behavior Reproduction Test: Compares the model's simulated behavior with real-world historical data. For instance, the model accurately simulates the retirement rate of experts over time (Figure 10), showing logical behavior.

Error Measurement Test: Quantifies the deviation between the model's simulated output and actual historical data. The model's predictions should closely match real-world data, indicating high accuracy.

5. Scenario Planning

In order to achieve the most important goal of modeling dynamic systems, it is necessary to investigate different potential policies for strengthening and improving the model's performance. Among the scenarios or the proposed policies, the policy providing the best result is selected for implementation in the desired system. For this reason, after measuring the model's validity and when the research experts reach a consensus, the results obtained from investigating the scenarios can be used to evaluate different policies to improve the system. For this purpose, in the present research, after validating the model, it was used to run a simulation experiment, and the results obtained are presented below. This research, considered eight scenarios, and the economic consequence or income was considered as the basis of scenario creation.

Examining several possible policies for enhancing and strengthening the model's performance is essential to achieving the main objective of modeling dynamic systems. The scenarios were created based on expert input and the key variables identified in the system dynamics model. Each scenario focuses on a specific aspect of the LARG paradigms, aiming to evaluate the impact of different strategies on the supply chain's performance.

(14) **Expert Consultation:** Experts from the automotive industry were consulted to identify the critical variables and parameters affecting the supply chain's performance.

- **Identification of Key Variables:** Variables such as resource utilization, network structure, product quality, process flexibility, supply chain efficiency, strategic alliances, and performance monitoring were identified as critical factors.
- **Scenario Definition:** Eight scenarios were defined to simulate the impact of changes in these key variables on the supply chain's performance. Each scenario focuses on strengthening a specific aspect, such as resource utilization, network structure, or process flexibility.
- **Simulation and Analysis:** The scenarios were simulated using the system dynamics model, and the results were analyzed to determine the impact on income and other performance metrics.

5.1. The level of income or economic consequences scenario by strengthening the utilization and optimal use of resources

In this scenario, the income is changed to an equal state. The simulation of the model about the level of income or economic consequences by strengthening the utilization and optimal use of resources shows that the optimal level of income by strengthening the utilization and optimal use of resources in the maximum state is more suitable than the equal state. In the equal state, it is more suitable than the current state. As can be seen in this scenario, the trend of changes from 1390 to 1398 (2011 to 2019) was not very noticeable, but from 1398 to the end of the simulation period, it faced an increasing trend and exponential growth, as shown in Figure 12.

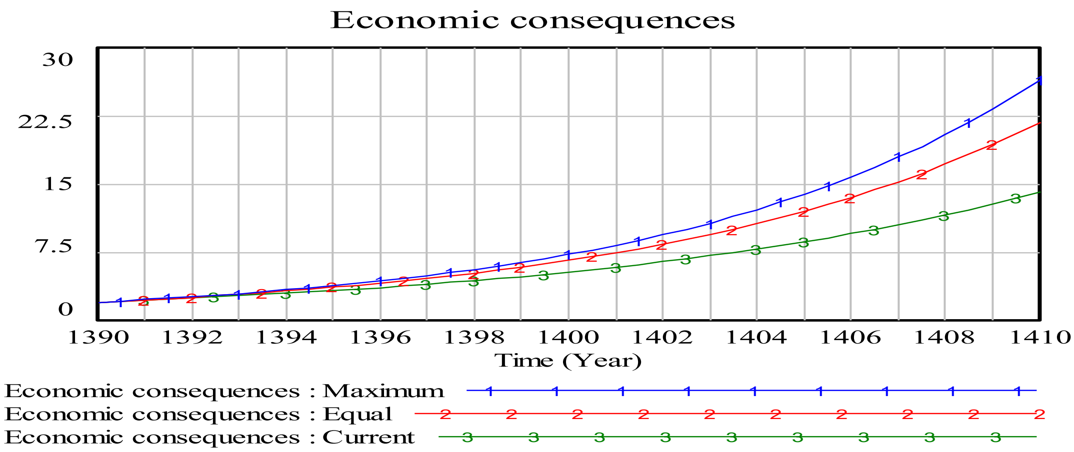

Figure 64. Simulation of the first scenario

5.2. The level of income or economic consequences scenario by strengthening the use of the network structure

In this scenario, the model simulation about the income level by strengthening the use of the network structure shows that the income level by strengthening the use of the network structure in the maximum state is better than the equal state. In the equal state, it is better than the current state. Of course, it is acknowledged that the distance between the equal state and the maximum state from the beginning of the simulation time to 1406 (2027) is very close, and from 1406 to the end of the period, there is almost a noticeable and significant increase as shown in Figure 13.

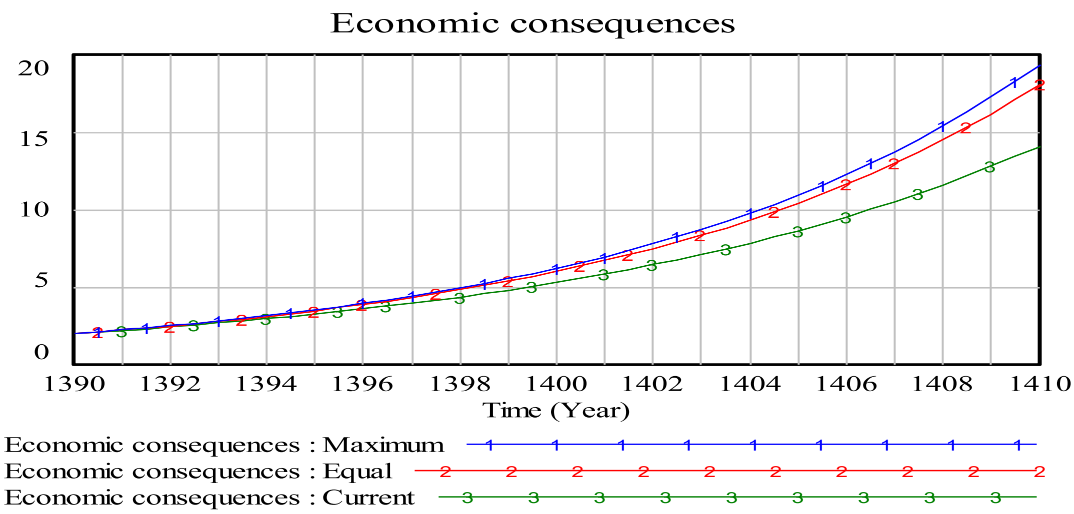

Figure 65. Simulation of the second scenario

5.3. The level of income scenario according to the quality of products and services

In this scenario, the simulation of the model about the level of economic consequences or income according to the quality of products and services shows that the level of income according to the quality of products and services in the maximum state is higher than in the equal state and in the equal state it is higher than the current state. Of course, it is acknowledged that the distance between the equal state and the maximum state from the beginning of the simulation period to the year 1406 is very close, and from the year 1406 to the end of the period, the increasing trend is almost noticeable, as shown in Figure 14.

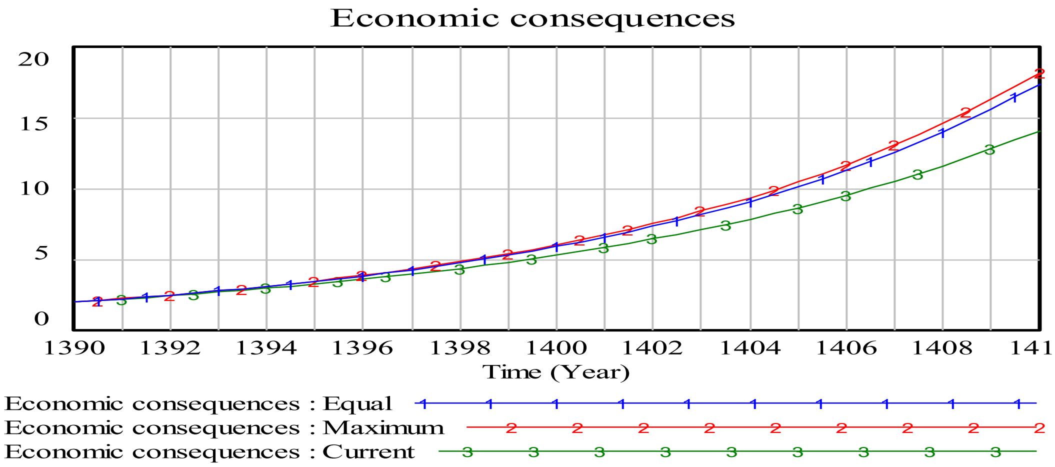

Figure 66. Simulation of the third scenario

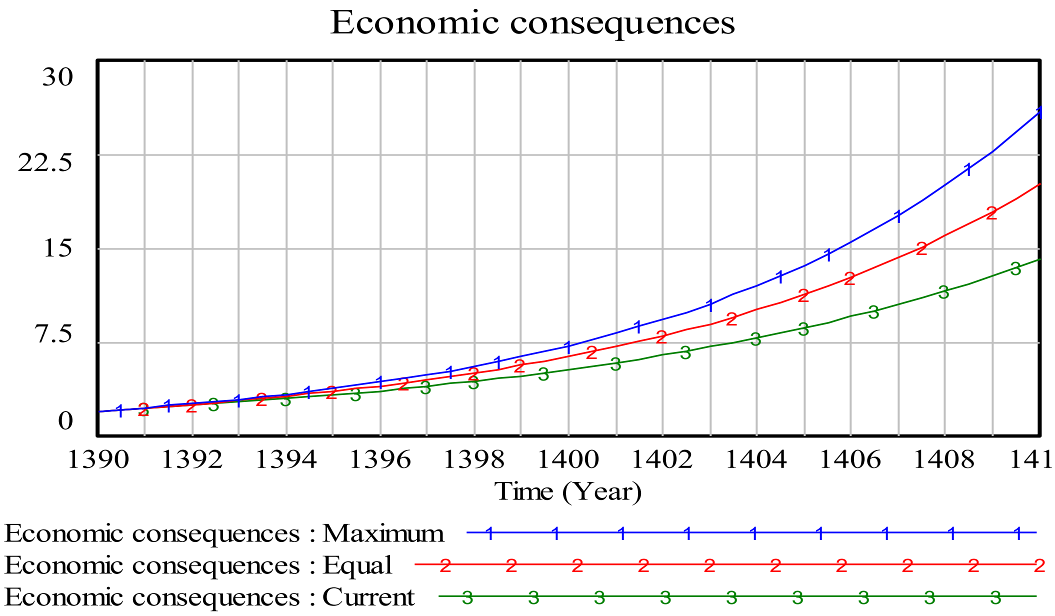

Figure 67. Simulation of the fourth scenario

5.4. The level of income scenario according to process flexibility

In this scenario, the simulation of the model about the level of income according to process flexibility shows that the level of income according to process flexibility in the maximum state is higher than in the equal state, and it is higher in the equal state than the current state. It should be noted that these changes from 1390 to 1400 (2011 to 2021) in the simulation period were not significant. However, from 1400 to the end of the simulation period, there is an increasing and noticeable trend, as shown in Figure 16.

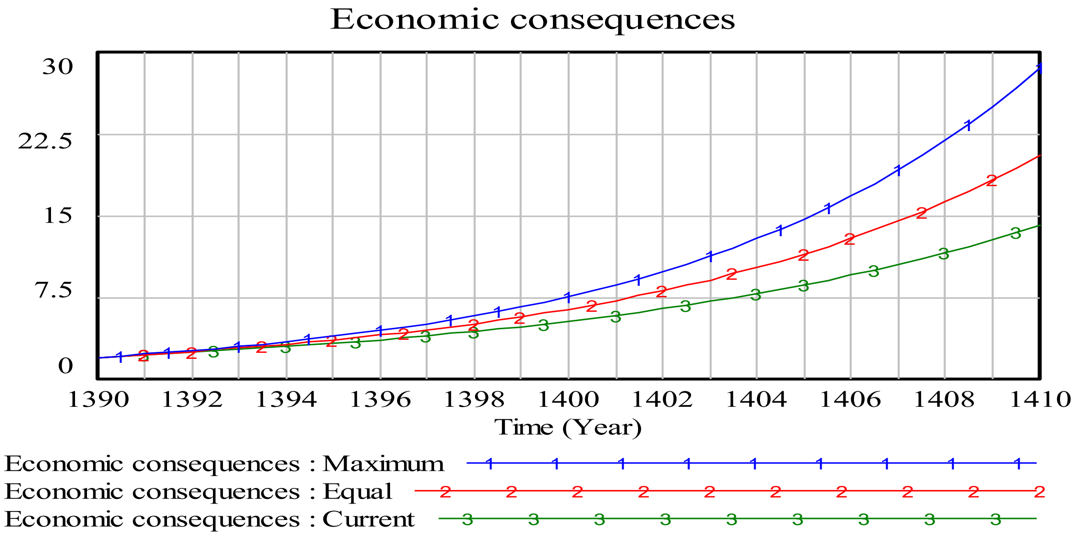

Figure 68. Simulation of the fifth scenario

5.5. The level of income scenario according to the efficiency of the supply chain

In this scenario, the simulation of the model regarding the level of income according to the efficiency of the supply chain shows that the level of income according to the efficiency of the supply chain in the maximum state is higher than the equal state and in the equal state it is higher than the current state. It should be noted that the difference between the simulations was not very noticeable in these changes from 1390 to 1396 (2011 to 2017). However, from 1396 to the end of the simulation period, the state of the maximum level of income related to the efficiency of the supply chain showed an increasing and noticeable trend, as shown in Figure 17.

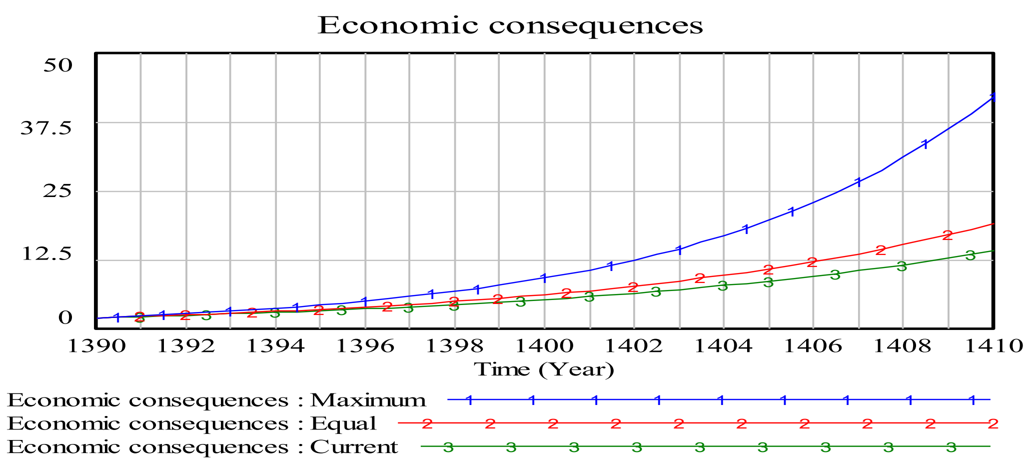

Figure 69. Simulation of the sixth scenario

5.6. The level of income scenario according to strategic alliance

In this scenario, the simulation of the model about the income level according to the strategic alliance shows that the income according to the strategic alliance is higher than the equal state in the maximum state and higher than the current state in the equal state. It should be noted that these changes from 1390 to 1400, the difference between the simulations was not very significant, but from 1401 (2022) to the end of the simulation period, the state of maximum income due to the strategic alliance has a noticeable increasing trend, as shown in Figure 18.

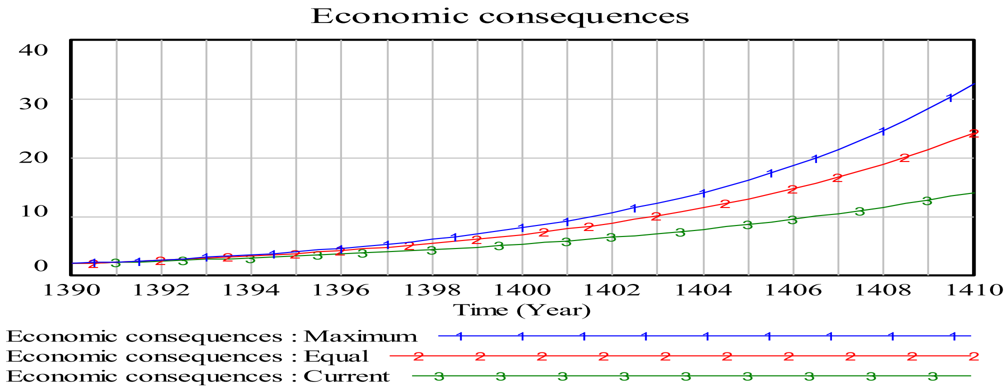

Figure 70. Simulation of the seventh scenario

5.7. The level of income scenario according to performance and monitoring factors

In this scenario, the simulation of the model regarding the income level according to the performance and monitoring factors shows that the income level according to performance and monitoring factors is higher in the maximum state than the equal state, and it is higher in the equal state than the current state. It should be noted that the difference between the simulations from 1390 to 1404 (2011 to 2025) was not very noticeable. However, from 1404 to the end of the simulation period, the state of the maximum income level has an increasing trend according to performance and monitoring factors (Figure 19).

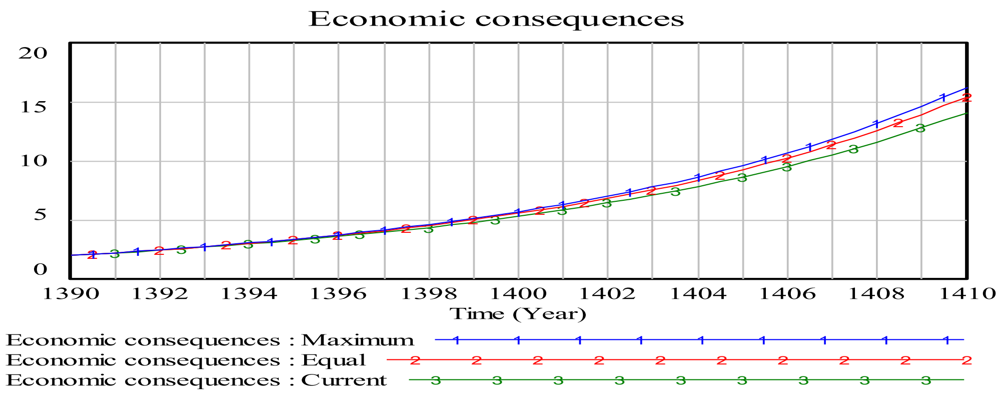

Figure 71. Simulation of the eighth scenario

6. Conclusion

In this research, a system dynamics model was proposed to implement paradigms related to LARG policy in the suppliers of SAIPA Company. For this purpose, first, the components of the research dynamic model were identified. Specific models of each paradigm were presented in each section related to the four paradigms. Finally, the research dynamic model was presented by combining four approaches (lean, agile, resilient, and green). It should be noted that to reach the final model of the research, four dynamic hypotheses were developed according to the four paradigms. In general, with these interpretations, 52 variables were identified in the dynamic model of the research, which included auxiliary, state, and flow variables. This model included 52 variables, comprising auxiliary, state, and flow variables, which were used to simulate eight different scenarios, as shown in Table 4.

Table 33. Summary of scenario analysis result

Scenario Number	Scenario Description	Reason for Results
1	Utilization and Optimal Use of Resources	Improved resource utilization leads to higher operational efficiency and cost savings, directly enhancingincome.
2	Use of Network Structure	Strengthening network structures enhances collaboration and information sharing, which improves overall supply chain coordination and performance.
3	Quality of Products and Services	High product and service quality increases customer satisfaction and loyalty, increasing sales and income.
4	Value Flow and Added Value Created	Efficient value flow and the creation of added value streamline processes and reduce waste, resulting in increased profitability.
5	Process Flexibility	Process flexibility allows for quicker adaptation to market changes and customer demands, leading to improved income levels.
6	Supply Chain Efficiency	Enhanced supply chain efficiency reduces costs and improves delivery times, significantly boosting income.
7	Strategic Alliance	Strategic alliances foster strong partnerships and collaboration, improving supply chain resilience and performance.
8	Performance and Monitoring Factors	Effective performance monitoring ensures continuous improvement and alignment with strategic goals, positively impacting income.

The highest income increase was observed in Scenario 6, emphasizing supply chain efficiency, followed by Scenario 5, focusing on process flexibility. Scenario 4 highlighted the importance of efficient value flow and added value in improving profitability. Scenarios 2 and 3 demonstrated the benefits of strong network structures and high product quality. According to the results obtained and the trend analysis of the graphs related to the research scenarios, the greatest change was related to the sixth scenario, which refers to the role of the supply chain's efficiency in increasing the income level. The next scenario is Scenario 5, referring to increasing the level of income due to process flexibility. In third place is Scenario 4, which refers to increasing the income level according to the value flow and added value created. For future research, it is suggested that a hybrid approach using a mathematical programming model and system dynamics be provided to analyze LARG paradigms. The research's key findings are:

- Enhancing supply chain efficiency significantly boosts income, underscoring the importance of optimizing processes and reducing costs.
- Flexibility allows quick adaptation to market changes, highlighting the need for dynamic and responsive supply chain strategies.
- Efficient value flow and added value creation improve profitability, emphasizing the need for continuous process improvement and waste reduction.
- Strong partnerships enhance resilience and performance, suggesting that companies should invest in building and maintaining strategic alliances.

According to the results, practical suggestions are as follows:

- Companies should optimize their supply chain processes to reduce costs and improve delivery times.
- Implementing flexible processes can help companies quickly adapt to market changes and customer demands.
- Building strong partnerships can enhance supply chain resilience and overall performance.

The model relies on historical data and expert input, which may not fully capture future uncertainties and market dynamics. The study focuses on the automotive industry, and findings may not be directly applicable to other industries without modifications. Future research could explore the integration of LARG paradigms with other supply chain management strategies, such as digitalization and Industry 4.0 technologies. Investigating the application of LARG paradigms in other industries, such as healthcare or electronics, can provide insights into their broader applicability and benefits. Developing hybrid models that combine mathematical programming with system dynamics can offer a more comprehensive analysis of LARG paradigms. Examining the impact of external factors, such as geopolitical changes and environmental regulations, on the implementation and effectiveness of LARG paradigms can provide valuable insights for practitioners.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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Journal of Systems Thinking in Practice
JSTINP, *QUARTERLY*
Homepage: jstinp.um.ac.ir
Online ISSN: 2821-1669, Print ISSN: 2980-9460
Research Article
DOI: 10.22067/JSTINP.2024.87413.1097
JSTINP 2024; Vol. 3, No. 4

Providing a Model of Customer Experience Management Based on Knowledge Management Models in the Field of Fintech Using Machine Learning

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How to cite this article

Rahmani, A., Sorouri, M., Radfar, R., Alborzi, M. 2024. Providing a Model of Customer Experience Management Based on Knowledge Management Models in the Field of Fintech Using Machine Learning. *Journal of Systems Thinking in Practice*, *3*(4), pp.132 -.159. doi: 10.22067/jstinp.2024.87413.1097.
URL: https://jstinp.um.ac.ir/article_45726.html.

ABSTRACT

This study explores the role of machine learning in managing knowledge of customer experience. Given the importance of high-quality knowledge for organizational innovation, this research aim is to address existing research gaps and propose a novel model for leveraging customer experiences in the fintech sector using machine learning. The main research question is to identify the key components and effective elements in developing a knowledge management of customer experience model using machine learning. Two secondary questions focus on identifying the most relevant knowledge management model for developing the knowledge management of customer experience model and assessing the suitability of machine learning capabilities for interpreting customer perceptions.
The research methodology is design science. Conceptual and structural equation models were developed, and hypotheses were tested and validated through model fitting. The findings led to the creation of a framework for future research and the development of the APO model into a seven-layer APO-CEM model, which includes preprocessing, coding, thematic categorization, and improved decision tree accuracy. The model was positioned and validated within the fintech ecosystem. Results confirm the model's effectiveness in enhancing growth, productivity, and customer satisfaction and demonstrate that machine learning can effectively measure and improve the quality of knowledge of customer experience through the cultivation of customer insights.

Keywords

Fintech, Knowledge management, Design science, Machine learning, Customer experience.

Article history

Received: 2024-04-09
Revised: 2024-08-05
Accepted: 2024-09-23
Published (Online): 2024-12-20

Number of Figures: 10 **Number of Tables: 11** **Number of Pages: 28** **Number of References:48**

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1. Introduction

In today's rapidly evolving business environment, knowledge has become crucial for organizations seeking a competitive advantage. Specifically, customer-related knowledge has evolved into a key concept, encompassing knowledge about the customer, knowledge for the customer, and knowledge from the customer (Alryalat et al., 2008). Since a significant portion of knowledge is inherently stored in the human brain, the performance and perceptions of individuals fundamentally drive organizational outcomes (Zhou et al., 2020). Effective knowledge management (KM) focuses not on managing all knowledge but on leveraging collective knowledge from employees, customers, and stakeholders to enhance performance through differentiated products and services, ultimately meeting customer expectations (Alryalat et al., 2008). Transforming efficient experiences and data into actionable knowledge positively impacts decision-making speed, strategy implementation, and innovation (Teran et al., 2021).Despite the importance of customer experience as a multidimensional concept analyzed from various perspectives and industries (Barbu et al., 2021), the ability to effectively disseminate acquired experiences is critical (Schneider, 2009). Previous research shows tacit knowledge is obtained from experience (Jaziri, 2019) .Tacit knowledge gained from experience forms the foundation for interpreting and applying knowledge at its highest level : wisdom (Sanzogni et al., 2017). Knowledge management of customer experience involves systematically using customer knowledge to enhance organizational performance (Teran et al., 2021). This concept can be framed as an extension of KM if it is consistently applied (Schneider, 2009). Customer knowledge is categorized into "knowledge for," "knowledge about," and "knowledge from" (Desouza et al., 2005). So, customer experience can be identified as an indicator for discovering, extracting, and exploiting knowledge in a new knowledge management model (Jaziri, 2019).

Digital transformation has catalyzed the rise of Fintech, revolutionizing financial services and banking (Suryono et al., 2020). Innovations in financial technologies have significantly advanced the fintech ecosystem, receiving substantial attention from industry and academia (Anshari et al., 2018). Fintech represents the future of banking and finance, leveraging technology to provide more efficient financial services (Jagtiani et al., 2018). Integrating artificial intelligence with Fintech has enabled more intelligent financial processing (Wen et al., 2012), while a positive relationship between KM processes and AI algorithms has been established (Alghanem et al., 2020). Machine learning, a subset of AI, facilitates the development of accurate predictive models from data (Teran et al., 2021). However, machine

 DOI: 10.22067/JSTINP.2024.87413.1097

learning algorithms find predicting customer experience outcomes challenging (Wen et al., 2012). Research highlights the significance of KM and decision tree algorithms for classifying knowledge quality and the advantages of applying machine learning in KM from theoretical and practical perspectives (Kaun et al., 2021).

1.1. Problem statement and innovation

Despite the advancements in Fintech and the potential of AI and machine learning, there needs to be a greater gap in the effective application of KM models specifically tailored for customer experience in the fintech domain. Current models often fail to integrate customer knowledge comprehensively and leverage it for enhanced organizational performance. This study aims to address this gap by developing the APO-CEM model, which integrates machine learning techniques to optimize customer experience management. This research's primary innovation lies in applying the APO-CEM model to systematically cultivate customer knowledge and assess its impact on growth, productivity, and satisfaction within the fintech ecosystem.

1.2. Research questions and hypotheses

The study investigates the following main questions and sub-questions:

Main Question:

RQ1: What are the primary and effective components in developing a knowledge management model for customer experience through machine learning?

Sub-Questions:

RQ2: Which KM models are most suitable for developing a knowledge management model for customer experience?

RQ3: Is the decision tree algorithm effective for interpreting customer experience perceptions based on KM models?

The research hypotheses include:

- Applying AI technology (machine learning) significantly positively affects customer knowledge cultivation.
- Implementing KM components significantly positively affects customer knowledge cultivation.
- Customer knowledge cultivation significantly enhances developing a knowledge management model for customer experience.
- Customer experience management significantly contributes to the development of a knowledge management model for customer experience.
- Developing a knowledge management model for customer experience significantly impacts growth, productivity, and customer satisfaction.
-

2. literature review

Nowadays, marketing focus has shifted from products to providing services based on customer experience, challenging researchers to enable organizations to play a strategic role in interacting with customers (Maklan and Klaus, 2011). The consumer experience is a lived, subjective which can be transformed knowledge resulting from physical, praxiological, and rhetoric dimensions; all are integrated under a dynamic interaction between the consumer, the object, and the situation" (Jaziri, 2019). As cited in Jaziri (2019), customers are heterogeneous in terms of identity and want to be different from others through their shopping experiences (Cinotti, 2007).

Providing and managing customer experience across various digital channels and networks, including the fintech area, is critical for achieving business success, leading to investments in customer experience tied to effective business outcomes (Izogo et al., 2018). Customer experience management requires reliable measurement of customer perceptions. It is challenging because most customers cannot accurately assess why an experience could be good or bad. More importantly, the volume of data involved exceeds human capacity for analysis (Tsai et al., 2018).

Customer experience management is a global approach that stresses the brand experience design (Jaziri, 2019). Market researchers have identified suitable criteria for customer experience based on cognitive and emotional evaluation and the value of the purchase process from the customer's point of view rather than merely customer expectations (Maklan and Klaus, 2011). The customer experiential knowledge management approach is the fundamental theoretical framework that advanced the conversion of customer experience data into customer experiential knowledge (CEK) (Jaziri, 2019).

Measuring and evaluating customer experience is complex, and the researcher must determine which features impact customer experience and which are most important (Maklan and Klaus, 2011). Customer experience (CX) and customer experience management (CXM) are key principles of the management strategy paradigm (Wetzels et al., 2023). Effective customer experience management emphasizes converting customer experience data into actionable knowledge for the company (Jaziri, 2019). It requires extracting and applying knowledge as a conceptual model using knowledge management techniques and artificial intelligence (Izogo et al., 2018).

Studies in the customer experience area show that the feelings and emotions resulting from customer experiences meet their needs and enhance the experience by identifying the consumer's identity (Jaziri, 2019). Tacit knowledge, derived from individual experience, is not easily transferable to others (Weller et al., 2016). Competitive advantages of knowledge management can be assured only if intellectual capital is understood as knowledge that can be extracted and creates value (Teran et al., 2021).

The knowledge management framework includes five main processes: creating knowledge, discovering knowledge, storing knowledge, applying knowledge, and sharing knowledge (Alghanem et al., 2020). However, a process for recognizing and interpreting human emotions has not yet been adequately developed, as it cannot be easily explained or modeled (Sanzogni et al., 2017). Despite this, artificial intelligence has made significant strides in evolving knowledge management (Pinker, 2005).

Knowledge management requires tools to assist in creating, documenting, and sharing knowledge. KM tools are used to facilitate knowledge management through IT-based solutions to improve organizational performance (Alghanem et al., 2020). However, discovering and sharing tacit and practical knowledge in a structured format remains challenging, as knowledge in people's minds is not easily formalized (Weller et al., 2016).

In this regard, Jaziri (2019) conceptualized the customer experiential knowledge management approach (CEKM) as the association of the knowledge management process with the customer service experience in order to enhance the future customer service experience or/and to create an experience offer. CEKM is based on the tacit knowledge related to customer experiential knowledge (Jaziri, 2019). Knowledge creation is an applicant learning process in which people use their existing knowledge or experiences to understand new issues (Shi, 2019).

Fintech represents a new financial industry that applies technology to improve financial activities (Suryono et al., 2020). Digitization has led to the emergence of fintech companies, which provide services such as money transfer, exchange services, payment, internet banking, mobile banking, and IVR services (Ulusoya et al., 2019). Since fintech primarily involves technology-based aspects like big data, artificial intelligence, distributed databases, cloud computing, and cybersecurity solutions, it is assumed that fintech companies possess advanced IT expertise and engage in IT development and financial software production (Dranev et al., 2019).

Fintech is a paradigm where information technology drives innovation in the financial industry, evolving continuously and potentially overshadowing traditional financial markets (Lee et al., 2017). Fintech is an ecosystem that supports entrepreneurs, and governments should focus on the quantity and quality of innovative companies in the financial sector (Wonglimpiyarat, 2018).

Fintech aims to transform financial interactions by reducing costs, improving service quality, and creating a diverse and sustainable financial vision (Lee et al., 2017). Financial policies play a crucial role in guiding the development of innovative financial technology systems (Wonglimpiyarat, 2018). Studies show that 83% of financial institutions believe various aspects of their business are at risk of losing new ideas. Thus, investing in fintech creates a competitive advantage (Lee et al., 2017).

The classification of innovation dimensions in fintech includes company type, innovation type, maturity level, value chain situation, and business ecosystem nature (Drasch et al., 2018). The fintech ecosystem comprises five elements: 1) Fintech startups (payment, wealth management, loans, financial collective participation, capital market, and fintech insurance); 2) Technology developers (big data analytics, cloud computing, cryptography, and social media developers); 3) The government (as a regulator and legislator); 4) Traditional financial institutions (banks, insurance companies, stock brokerage firms, and investors) (Lee et al., 2017).

By focusing on technological advancements, fintech improves financial operations and is often delivered through mobile applications (Gai et al., 2018). Challenges in fintech include investment management, customer management, regulatory compliance, IT integration, privacy and security, and risk management (Lee et al., 2017). Fintech companies create opportunities for new financial products and solutions using innovative technologies (Gomber et al., 2017). Various knowledge management models exist, and the APO framework ensures that no crucial element is overlooked during implementation (Cahyaningsih et al., 2017). The APO framework defines knowledge management as a five-step process: 1) knowledge identification: 2) knowledge creation: 3) knowledge storage: 4) knowledge sharing: 5) knowledge application (Young, 2020). Additionally, the APO framework evaluates knowledge management and identifies areas for organizational focus (Khajouei et al., 2017).

Table 34. Summary of literature review on customer experience management and fintech innovations

Topic	Summary	References
Focus on Customer Experience	Shift from products to services based on customer experience, emphasizing its importance in strategic customer interactions.	Maklan and Klaus (2011)
Customer Experience Management	There is aneed to provide and manage customer experience across digital channels, including fintech, to achieve business success and effective outcomes.	Izogo et al. (2018)
Knowledge Management Models	Knowledge management includes five main processes: identification, creation, storage, sharing, and application of knowledge.	Alghanem et al. (2020)
APO Model	The APO model includes five stages: knowledge identification, creation, storage, sharing, and application	Young (2020)
Fintech Innovations	With advancements in AI and big data, fintech applies technology to improve financial activities. Fintech introduces new paradigms and challenges in the financial industry.	Suryono et al., (2020); Dranev et al., (2019)
Coordination and Engagement	More coordination with customers and customer engagement positively influence business customer experience.	Ruiz-Alba et al., (2023)
AI and Customer Experience	The connection between AI and customer experience is under-researched. Conversational AI models can impact customer experience, but further research is needed.	Abdelkader, (2023)

Figure 72. The APO knowledge management framework (Cahyaningsih et al., 2017)

Interpreting customer experience perception is crucial (Virginia et al., 2014). However, many companies have neglected this important issue, believing implementing customer experience perception correctly conflicts with purely human analysis and individual interpretation (Teran et al., 2019). A significant issue leading to the development of ineffective knowledge-based systems is the inadequate understanding of knowledge quality characteristics (Abdelrahman, 2019). Machine learning, a subset of AI, is a technique that can enhance knowledge quality and manage it more effectively (Malik et al., 2019). Human experiences, emotions, and perceptions are rooted in tacit knowledge that can inspire the development of new ideas (Busch, 2008).

Previous studies on the relationship between knowledge management processes and artificial intelligence systems indicate that the role of knowledge management processes and their impact on AI systems has been underexplored (Alghanem et al., 2020). Machine learning algorithms can potentially reduce costs associated with credit and operational decisions in fintech (Jagtiani et al., 2018). AI addresses customer expectations by extracting optimal results from fintech ecosystem databases (Hoeschel et al., 2006). Machine learning is valuable for knowledge management, and the decision tree algorithm shows strong potential in classifying knowledge quality (Kaun et al., 2021). Knowledge analysis is closely tied to various learning processes (Teran et al., 2021), and AI and KM are intricately related to the nature of knowledge (Sanzogni et al., 2017).

One of the most common and straightforward machine learning algorithms is the decision tree, known for its interpretability, efficiency, and flexibility in handling customer perceptions (Lamrini, 2020). Implementing the decision tree algorithm for classifying knowledge quality and machine learning's effect on knowledge-based systems proves effective in knowledge management (Kaun et al., 2021). The decision tree is a supervised learning algorithm valued for its interpretability, which aids users in making decisions based on interpreted perceptions (Lamrini, 2020). Among programming languages, Python is highly compatible with machine learning algorithms and offers visualization tools for this purpose (Raschka et al., 2020). The necessity of developing models and theorizing in fintech research subjects, machine learning, and customer experience management has been consolidated in previous studies (Rahmani et al., 2022). Enhanced coordination with customers and customer engagement positively influence business customer experience (Ruiz-Alba et al., 2023). Additionally, while the connection between AI and customer experience is infrequently studied, conversational AI models have the potential to positively impact these aspects. Further research is needed to understand the specific factors influencing the impact of conversational AI models on customer experience (Abdelkader, 2023).

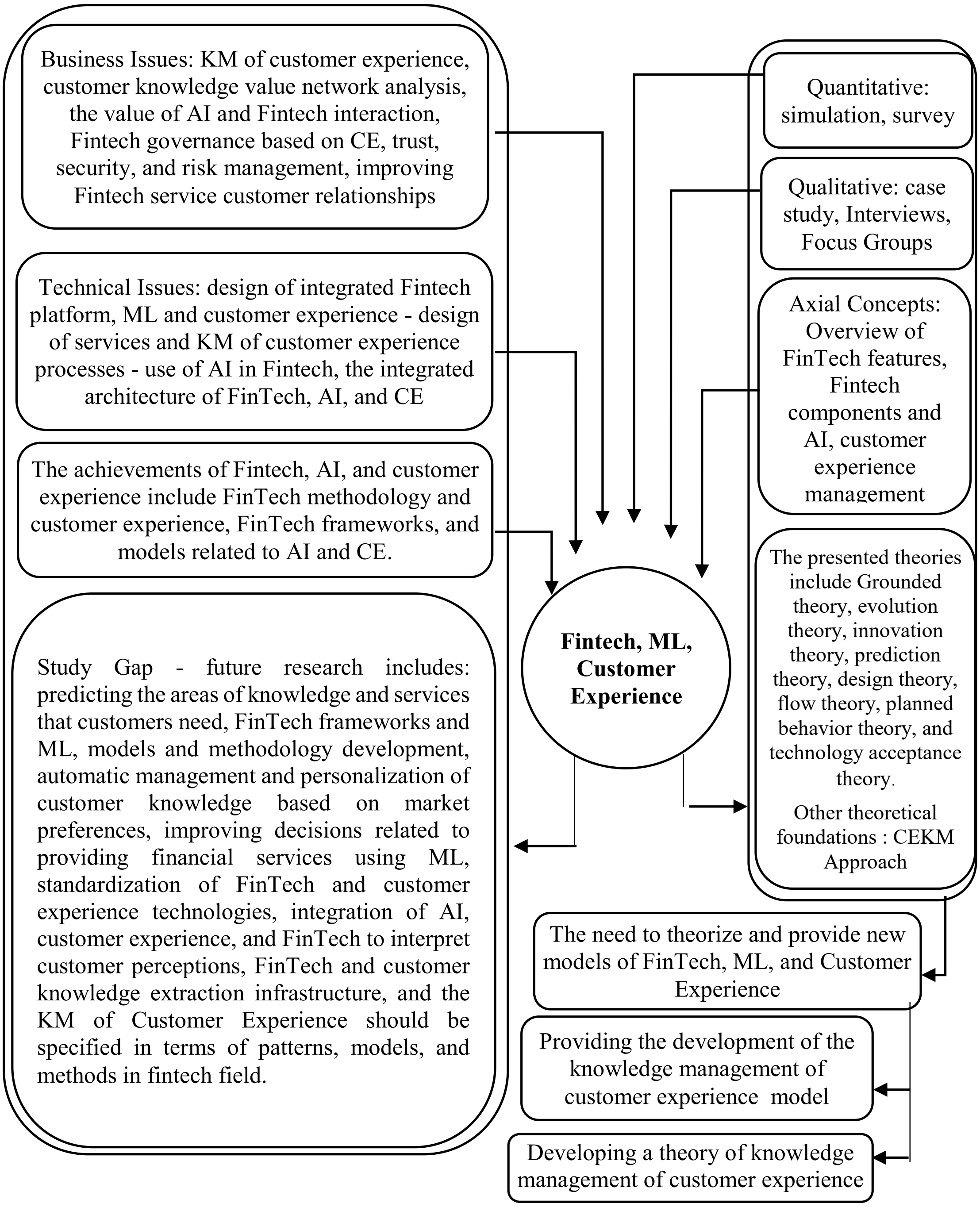

Figure 73. The proposed framework for the research in fintech, machine learning, and customer experience area (Rahmani et al., 2022).

3. Methodology

The research seeks to provide a customer experience management model based on a knowledge management model through machine learning in the fintech ecosystem. The research method is design science. The type of research in terms of purpose is applied. The customer experience data analysis segment is viewed as a quantitative undertaking based on artificial intelligence (machine learning). The interpretation section is based on interviews and will follow the design science method in a structured way. The research includes twelve main stages.First, to review the literature, selecting and processing articles was designed and used. Second, by identifying quality knowledge in the data obtained from the customers' experiences in the fintech area, the relationship between knowledge management and customer experience management and the relationship between knowledge management and machine learning were studied, and the research questions were determined. Third, the conceptual model was designed, the relationship between the model's components was determined, and the hypotheses were identified. In the fourth stage, the design of structural equation modeling, the questionnaire, validity and reliability, and the test and fitting of the model were carried out, and the significance level of the hypotheses was measured.

Fifth, the APO model was selected as the most appropriate model for classifying knowledge quality. Sixth, the data sets required for training and testing the decision tree algorithm were identified and coded, and the decision tree was drawn, modeled, and tested using the Python language and the VS-Code platform. Seventh, the research proposed model, APO-CEM, was designed as a new development of the APO model. The APO-CEM model was embedded in the fintech conceptual ecosystem in the eighth step. Ninth, the research questions were answered by analyzing the data .Tenth, the results from the perspective of theoretical and practical concepts were discussed. In the eleventh stage, the research concluded by pointing out the research limitations and suggestions for future research.

Drawing the processing processes is essential for studying and reviewing papers (Petersen et al., 2015). So, first, the process map of selection and review of sources for the research was designed—figure 3.

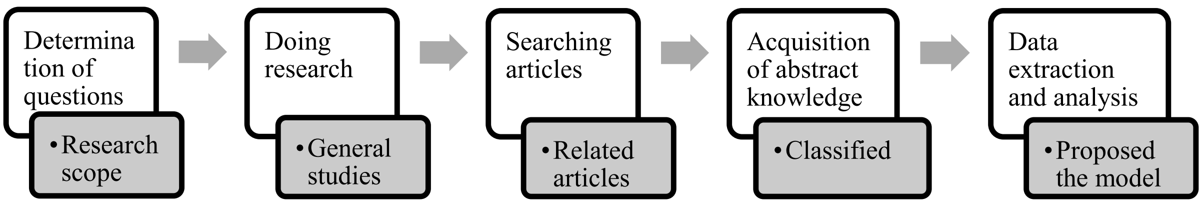

Figure 74. Process map of selection and review of articles

After reviewing 75 credible articles, 45 articles were selected as main and most related references. Next, the research conceptual model was designed, and a questionnaire consisting of seven constructs and thirty questions was designed. The construct titles include 1) Productivity and customer satisfaction, 2) Perception analysis, 3) Application of KM components, 4) Usage of AI technology, 5) Development of knowledge management of customer experience model, 6) Customer experience management, and 7) Cultivating customer knowledge. In the end, five hypotheses were predicted.

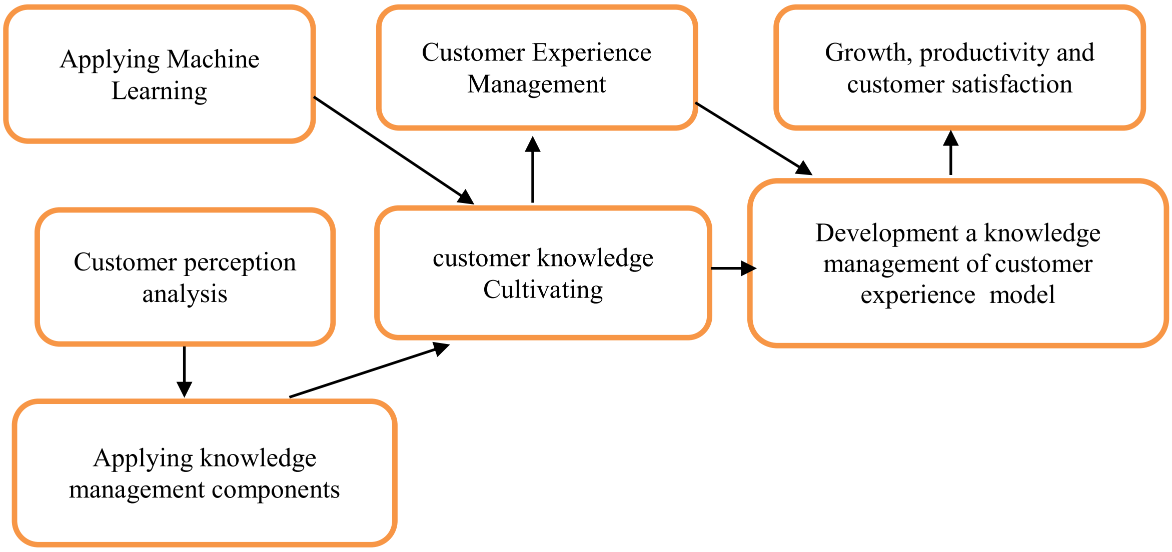

Figure 75. The research conceptual model

In the following, the data were processed and coded. The structural equation model was designed by SmartPLS, tested, and validated to validate the obtained results. Then, the reliability and model fit were examined and accepted. The target society in the research is the opinions of fintech users, which were prepared through the Dataheart website. The dataset contains 831 comments related to the 2021-to-2022 years, which users shared.

Data preprocessing (customers' opinions and experiences) was done through review preprocessing and using the "nltk" library. It includes: a) All text was converted to lowercase. b) The words with no emotional load were removed. Next, the feature vectors based on the clean data set were created for each clean text to classify and use in machine learning.

The steps of sentiment analysis using machine learning are presented in Table 2. This process typically involves several key stages: data collection, preprocessing (such as tokenization and removing stop words), feature extraction, model training using labeled data, and testing the model's accuracy. The final output is a sentiment classification (positive, negative, or neutral) based on the learned patterns in the data.

Table 35. Pseudo code of sentiment analysis using machine learning

1	**Phase 1:Preprocessing**

2	Input: Dataset
3	Outputs:Optimize comments
4	Opinion tokenization
5	Stop word removal
6	Symbols removal
7	Spell correction
8	Stemming (Lemmatization)
9	**Phase 2: Classification**
10	Input:Optimize comments
11	Outputs: Computing comments
12	Classification opinion with vectorize method
13	**Phase 3: Sentiments analyzing**
14	Inputs: Labeled comments matrix
15	Outputs: Sentiment's analysis comments
16	Sentiments Analysis by decision three algorithm
17	**Phase 4:Accuracy optomization**
18	Tuning hyperparameters

In the preprocessing stage, as shown in Table 3, customer feedback in the FinTech domain was collected, analyzed, and coded. This feedback was processed and visualized using Python programming and Visual Studio Code, leveraging natural language processing (NLP) methods and a decision tree model to analyze customer perceptions.In the quantitative research section, sentiment analysis techniques were employed. First, a customer feedback table was prepared, and numerical values were assigned to each feedback item, as illustrated in Table 4. Subsequently, customer perceptions were categorized based on these values, and relevant insights were extracted, as shown in Table 5. After preparing the dataset, the decision tree model was constructed for data analysis and prediction, as depicted in Table 6. Finally, by adjusting the hyperparameters of the model, the accuracy of the decision tree algorithm increased from 86% to 89%. This improvement demonstrates the enhanced efficiency of the algorithm in analyzing customer data.

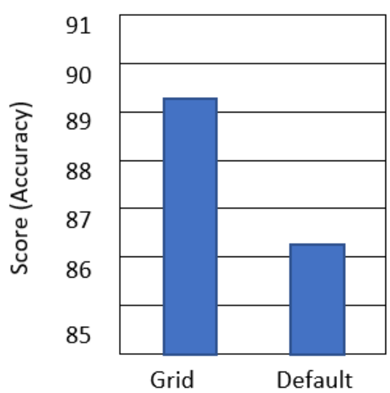

Figure 76. Comparison of the accuracy value in the optimal and default state for the decision tree

Table 36. Example of coding table and comments tag of fintech users, entrance for decision tree

Variable	**Tag (Dependent variable)**			
	0	1	2	3
Service speed	Excellent	Very Good	Average	Bad
Service quality	Very satisfied	Satisfied	Good	Poor
Performance quality	High quality	Acceptable	low quality	Awful
Brand trust	Authentic	Well-Known	Fake	Unknown
Innovation	High Tech	Very latest	New	Old

Table 37. Example of the dataset

Service speed	Excellent	It's great in every way	0
	Very Good	Thanks to (Fintech name)	1
	Average	Received late	2
	Bad	Finished	3
Service quality	Very satisfied	Really satisfied - full satisfaction - excellent in every way	0
	Satisfied	Not bad - I am satisfied - acceptable	1
	Good	Well - very well - worth it	2
	Poor	It is not recommended at all	3
Performance quality	High quality	Excellent - Excellent in every way	0
	Acceptable	Not Bad- So So	1
	low quality	Useless- Out of service	2
	Awful	Don't buy - Wrong purchase	3
Brand trust	Authentic	Prestigious - Valuable and authentic	0
	Well-Known	Well-known brand	1
	Fake	Fake–copy brand	2
	Unknown	Anonymous -nameless - unknown brand	3
Innovation	High Tech	Very advanced	0
	Very latest	Excellent - high technology - latest version	1
	New	Good appearance - High copy	2
	Old	It's no different - like the previous ones –old version	3

Table 38. Definition of variables and nodes

Row	**Variable name**	**Variable concept**	**Thematic category**	**Abundance**
1	Service speed	The need for the creation of customer satisfaction	360 customer experiences, Customization	%12
2	Service quality	The need for optimization	Personalization, 360 customer experiences	%27
3	Performance quality	The need for optimization	Customization	%17
4	Brand trust	The necessity of brand development	360 customer experiences	%18
5	Innovation	The need for innovation	Customization, personalization	%26
Customization = 31%		Customer experience 360 = 22%	Personalization = 35%	

Table 39. Sample of the final coded dataset

Services Speed	Service quality	Performance quality	Brand trust	Innovation
0	1	0	1	2
0	0	0	1	0
1	0	0	0	0
1	3	3	3	2
1	1	1	3	2
3	3	3	3	3
0	1	1	2	3
2	3	3	1	0
3	3	3	2	1
1	2	1	3	3

By drawing a decision tree, customer needs were determined, and customer experience knowledge was modeled. Among the machine learning algorithms, the decision tree is one of the most common and simplest ones, with three notable features—interpretability, efficiency, and flexibility of customer perceptions (Lamrini, 2020). Finally, the acceptance status of the hypotheses was determined, and the questions were answered.

4. Results

The data collection was carried out using a questionnaire prepared by the researchers. The questionnaire was designed to evaluate the conceptual model of knowledge management of customer experience, focusing on using knowledge management and machine learning components to enhance customer knowledge and assess the model's effectiveness in growth, productivity, and customer satisfaction. The questionnaire consists of two main parts. The first part includes demographic information of the statistical population, including gender, age, years of work, and level of education. The second part consists of 30 questions related to 7 main constructs: 1) Customer perceptions, 2) Customer experience management, 3) Knowledge management components, 4) Customer knowledge cultivation, 5) Applying AI technology, 6) Growth, productivity, and customer satisfaction, and 7) Development of a model for knowledge management of customer experience.

The validity of the questionnaire was assessed using divergent and convergent methods, and construct validity was evaluated through Confirmatory Factor Analysis (CFA). For all dimensions, Cronbach's Alpha was calculated to be above 0.7; for the entire questionnaire, it was 0.80, which is considered acceptable. The combined reliability coefficient (CR), calculated using SEM and PLS software, was also examined. The values of Cronbach's Alpha and CR for each dimension are shown in Table 7, confirming the reliability of the questionnaire.

Table 40. The composition of questionnaire questions, cronbach's alpha, and CR values

	Construct	Questions NO	Cronbach's alpha	CR	Total
Knowledge management of customer experience	Growth, productivity, and customer satisfaction	1 to 5	0.753	0.864	**80%**
	Customer perceptions Analysis	6 to 9	0.902	0.921	
	Applying knowledge management components	10 to 12	0.822	0.896	
	Using AI technology-ML	13 to 17	0.793	0.801	
	Development of knowledge management of customer experience model	18 to 22	0.750	0.816	
	Customer Experience Management	23 to 26	0.711	0.814	
	Cultivating knowledge of customer experience	27 to 30	0.828	0.887	

The measurement scale of the questions was based on a 5-point Likert scale, with scores ranging from 1 (very little) to 5 (very much). The impact of each of the 30 indicators on the knowledge management of customer experience was assessed. Factors were identified based on theoretical foundations and interviews with experts in the field. For convergent validity, the Average Variance Extracted (AVE) was used. As shown in Table 8, all AVE values for the constructs exceed 0.5, confirming the convergent validity of the questionnaire to an acceptable level. A matrix was created to calculate divergent validity by comparing the squared AVE of each construct with the correlation coefficients between constructs. This matrix, shown in Table 9, demonstrates that the squared AVE of each construct is greater than the correlation coefficients with other constructs, indicating the acceptability of the constructs' divergent validity.

Table 41. Convergent validity values

Construct	AVE
Growth, productivity, and customer satisfaction	0.693
Customer perceptions Analysis	0.751
Applying knowledge management components	0.743
Using AI technology-Machine Learning	0.518
Development of knowledge management of customer experience model	0.530
Customer Experience Management	0.524
Cultivating knowledge of customer experience	0.667

Table 42. Divergent validity values

Factors Influencing on knowledge Management of Customer Experience / **Factors influencing on knowledge management of customer experience**	Using AI technology-Machine Learning	Appling KM components	Customer perceptions Analysis	Development of knowledge management of customer experience model	Growth, productivity, and customer satisfaction	Customer Experience Management	Cultivating knowledge of customer experience
Using AI technology-Machine Learning	0.719						
Appling KM components	0.122	0.862					
Customer perceptions Analysis	0.126	0.330	0.866				
Development of knowledge management of customer experience model	0.715	-0.231	-0.103	0.728			
Growth, productivity, and customer satisfaction	0.414	0.137	0.176	0.585	0.832		
Customer Experience Management	0.348	-0.334	-0,031	0.672	0.395	0.724	
Cultivating knowledge of customer experience	0.367	0.442	0.177	0.177	0.208	-0.203	0.816

Confirmatory factor analysis was used for model fitting. The result of running the model by Smart PLS software is shown in Figure 6 in a meaningful state. As Table 10 shows all t-test values are higher than 1.96, and the confidence level above 95% is confirmed.

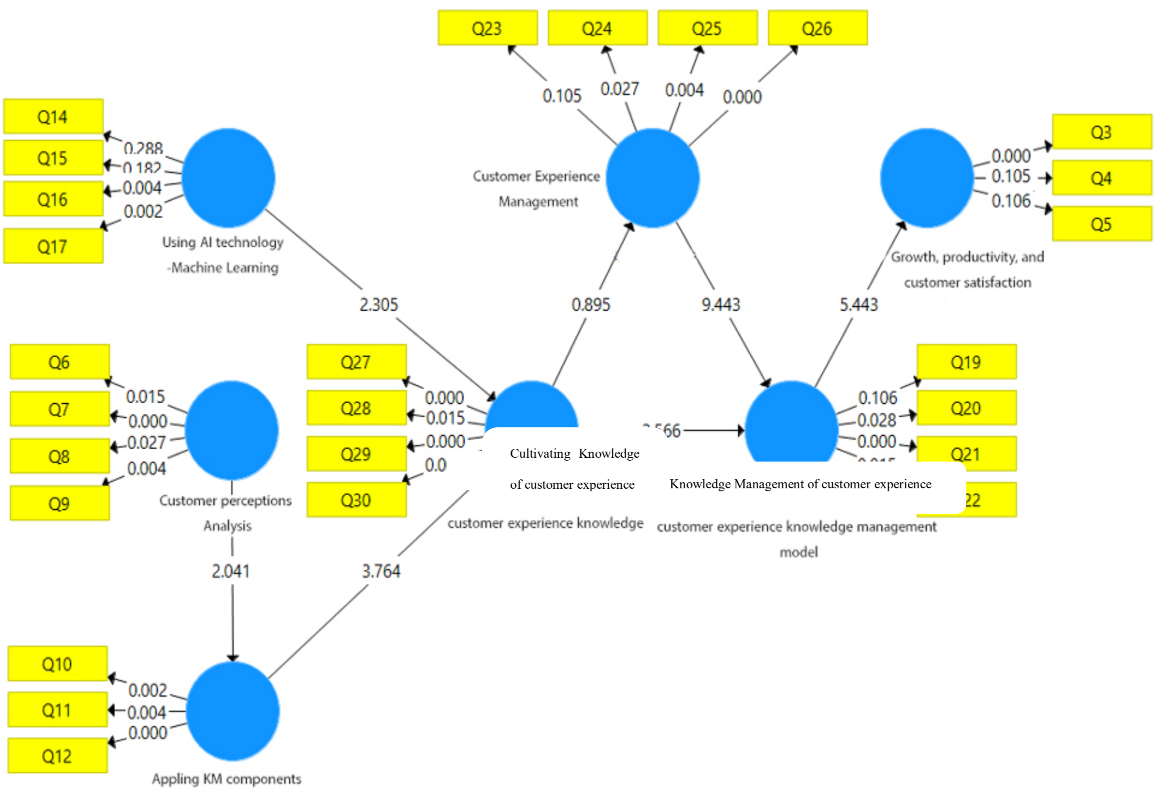

Figure 77. The research model in a meaningful state

For the research model, the standard estimation state was alsorun by Smart PLS. All factor loadings related to the questions were determined to be more than 0.4 and showed the strong influence of the effective indicators on customer knowledge management. The result is shown in Figure 7. Out of 30 questions, 26 indicators have a factor loading greater than 0.4, confirming the significance of their influence and showingthat the model has sufficient fit.

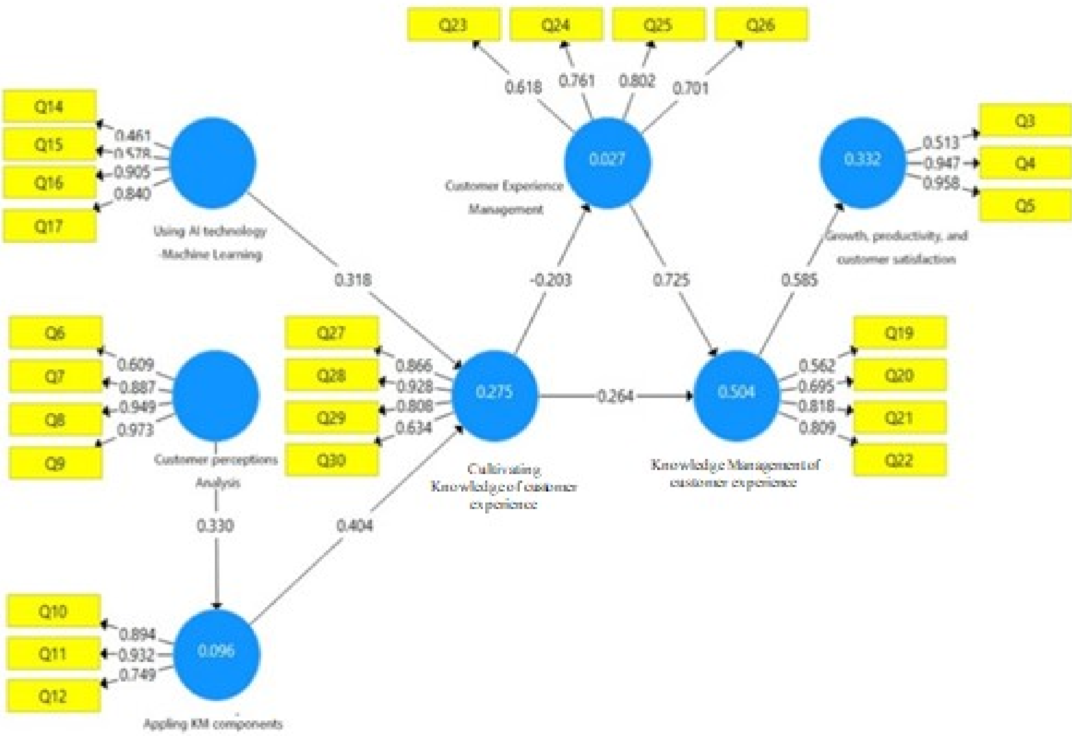

Figure 78. Research model in standard estimation state

The independent variables include the variable of applying AI-ML and the variable of customer perceptions analysis. The rest of the variables are dependent variables. The regression coefficients show that the hidden variable of customer experience management has the greatest impact on the hidden variable of development of the customer experience management model with a coefficient of 0.725. Also, developing the customer experience management model has a good effect on growth, productivity, and customer satisfaction, with a coefficient of 0.585. Only cultivating knowledge of customer experience has a negative and opposite effect on customer experience management. The model shows that the knowledge of the customer experience cultivation variable and the customer experience management variable explain and cover 50% of the variable of development of the customer experience management model. Also, the development variable of the customer experience management model explains 32% of the growth, productivity, and customer satisfaction variables.

4.1. *Path analysis*

The regression coefficients in the model for the determined hypotheses are all above 0.3, and the coefficients are in the significant range (Table 10). Also, the fitting indices in Table 11 show that the model fits well**.**

Table 43. The meaningful index values

Meaningful index	**t-test statistic t >1.96**	**Regression coefficient >0.3**
Applying AI-ML -> Customer knowledge cultivation	2.305	0.318
Applying KM components ->Customer knowledge cultivation	3.764	0.404
Development of knowledge management of customer experience model -> growth, productivity, and customer satisfaction	5.443	0.585
Customer Experience Management -> Development of knowledge management of customer experience model	6.443	0.725
Customer Knowledge Cultivation -> Development of Knowledge management of customer experience Model	2.566	0.264

4.2. *Significance of hypotheses*

In a significant state with a confidence level of 95%, all the obtained t-values were more than 1.96, so all the research hypotheses were evaluated as significant. The regression coefficients in this model for the determined hypotheses are above 3%, and the coefficients are in the significant range.

1. Applying AI-ML has a significant positive impact on customer knowledge cultivation .
2. Applying knowledge management components significantly positively impacts customer knowledge cultivation.
3. Customer knowledge Cultivation significantly impacts the knowledge management of customer experience model development.
4. Customer experience management has a significant positive impact on developing the knowledge management of the customer experience model .
5. The development of the knowledge management of the customer experience model significantly impacts growth, productivity, and customer satisfaction.

4.3. *Model fitting*

In order to model fitting, the Partial Least Squares method was used.

R-squared correlation: In the research, the model predictive power for variables of the development of knowledge management of customer experience model is evaluated, 518% value, and for the variable of growth, productivity, and customer satisfaction, the value is 342%, which was considered medium to high.

F Square: In the research model, the predictive power of the development of the knowledge management of customer experience model is evaluated with a strong value of 519%, and the variable of applying KM components with a value of 228% is evaluated as moderate.

Predictive correlation index Q2: In the research model, the predictive power of the model in internal constructs all have positive values, and model fitting was evaluated as good.

Model Fit:

Table 44. Model fitting results

SRMR	d_ULS	d_G	Chi-Square	NFI
0.010	0.465	0.263	138.95	0.757

Goodness of fit (GOF) Index: GOF = √average (AVE) × average (R2))

The calculated value for GOF is equal to 37.7%, which is higher than the value of 36%, so the model overall fit was evaluated as strong.

Normalized chi-square fit index x2/d.f (Acceptance limit > 1) : the value for the research model is equal to 1.33, which is more than the value of 1 and was approved.

4.4. Decision tree

The decision tree, with a depth of 5 and 81% accuracy, was drawn to clarify how to predict the target class (knowledge innovation) as a root node through Python in machine learning.

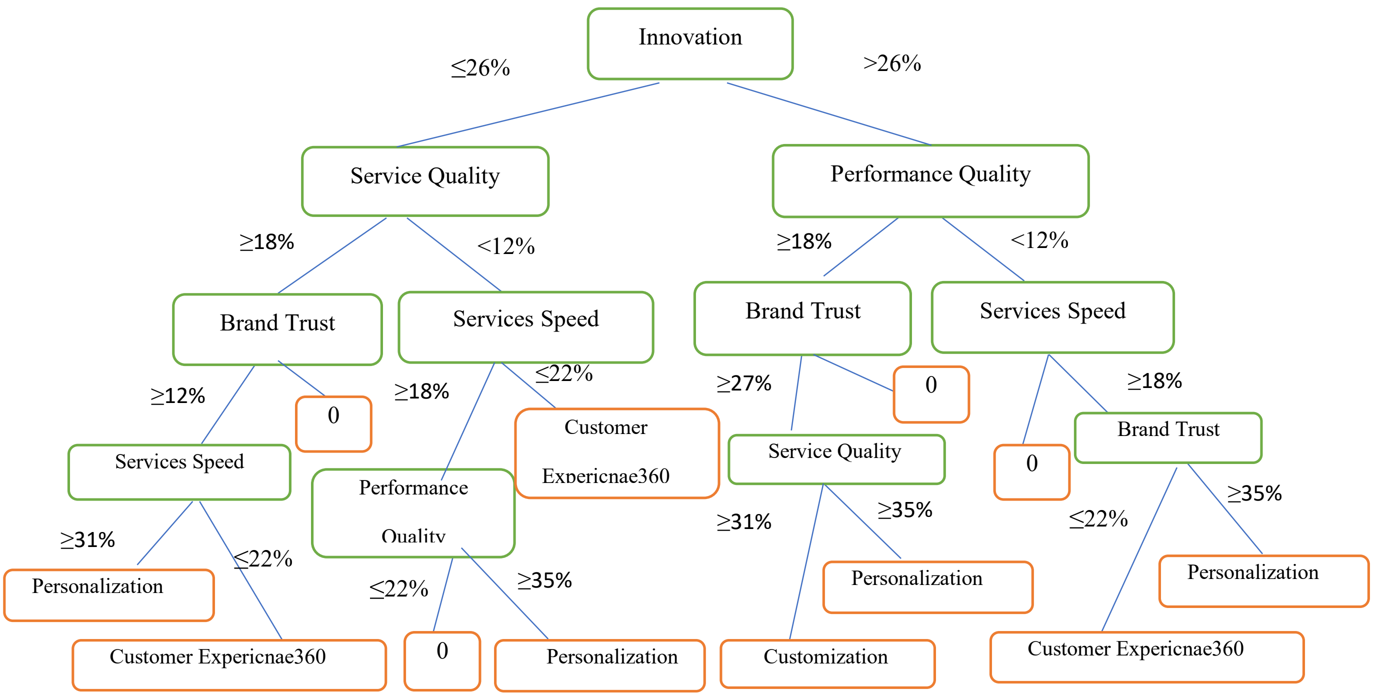

Figure 79. The drawn decision tree based on knowledge management of customer experience components

DOI: 10.22067/JSTINP.2024.87413.1097

4.4.1. Rule of decision tree

1- If the value of innovation is smaller than 26%, the value of performance quality is smaller than 12%, the value of service speed is greater than or equal to 18%, and the value of brand trust is greater than or equal to 35%, then the innovation goes towards Personalization.
2- If the value of innovation is smaller than 26%, the value of performance quality is smaller than 12%, the value of service speed is greater than or equal to 18%, and brand trust is smaller than or equal to 22%. The innovation goes towards Customer Experience 360.
3- If the value of innovation is smaller than 26%, the value of performance quality is greater than 18%, the value of brand trust is greater than 27%, and the value of service quality is greater than 35%, then the innovation goes towards Personalization.
4- If the value of innovation is smaller than 26%, the value of performance quality is greater than 18%, the value of brand trust is greater than or equal to 27%, and the value of service quality is smaller than 31%, then the innovation goes towards Customization.
5- If the value of innovation is greater than 26%, the value of service quality is smaller than 12%,. The value of service speed is smaller than 22%, then the innovation goes towards Customer Experience 360.
6- If the value of innovation is greater than 26%, the value of service quality is smaller than 12%, the value of service speed is greater than 18%, and the value of performance quality is greater than 35%, then the innovation goes towards Personalization.
7- If the value of innovation is greater than or equal to 26%, the value of service quality is greater than or equal to 18%, the value of the brand trust is greater than or equal to 12%, the value of service speed is smaller than or equal to 22%. The innovation goes towards Customer Experience 360.
8- If the value of innovation is greater than or equal to 26%, the service quality is greater than or equal to 18%, the brand trust is greater than or equal to 12%, and the service speed is greater than or equal to 31%, then innovation goes towards customization.

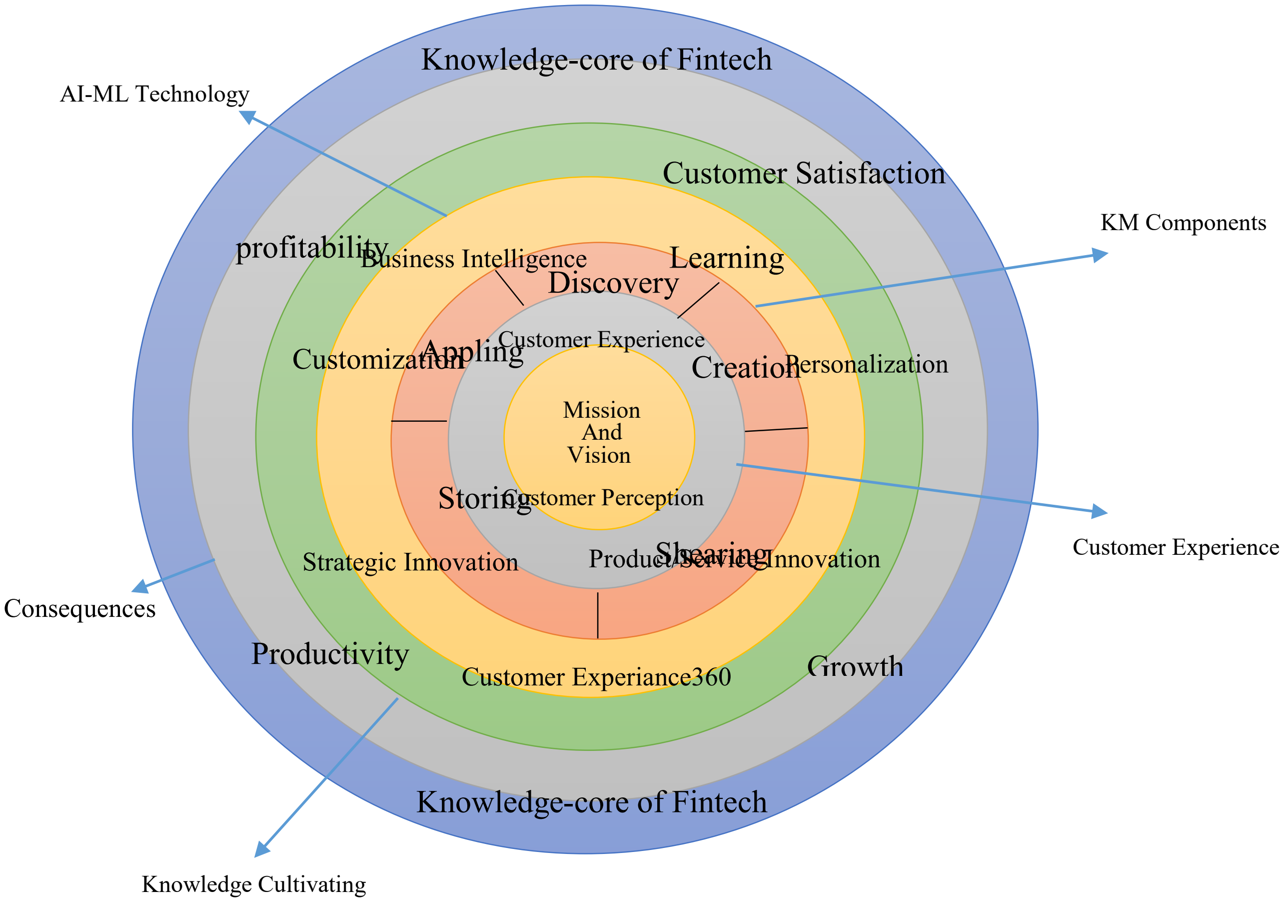

Figure 80. The research proposed model - Knowledge management of customer experience model APO-CEM

Here, the reasoning behind the algorithm used to reach the presented results is demonstrated. The rules have a logical structure. At the optimal level of data management of customer experiences, Personalization, Customization, and Customer Experience 360 are predicted with a probability of 97%. Consequently, through the proposed APO-CEM model, it is possible to acquire and store practical or tacit knowledge from customer experiences and cultivate it through AI to enhance the capabilities of Customization, Personalization, and Customer Experience 360. Indeed, Fintech service providers could utilize the cultivated knowledge to meet customers' needs, which can be shared with other customers.

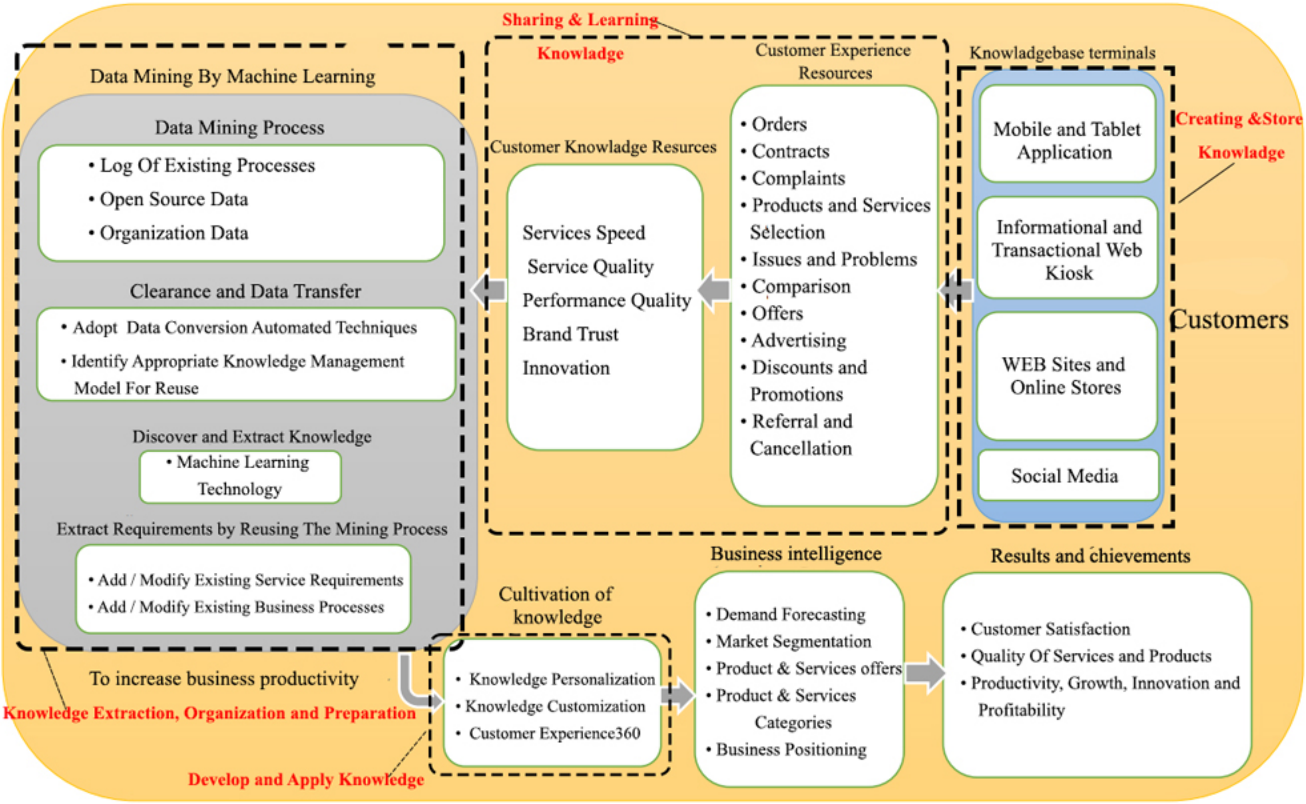

Figure 81. The APO-CEM model layout in the fintech ecosystem

The layout of the APO-CEM model in the fintech ecosystem, as shown in Figure 10, illustrates how different types of customers in fintech interact with services through knowledge terminals such as mobile applications, informational and transactional kiosks, fintech websites, and social networks. This interaction is where fintech customer experiences are created and stored. The customer experience resources include customer actions and perceptions related to ordering methods, contract types, service or product choices, product and service comparisons, complaints, comments, and personal experiences. These are evaluated through components such as performance quality, service quality, service speed, brand trust, and innovation, which collectively form the resources of customer knowledge.

In the next step, data mining and machine learning technologies are used to discover and extract customer experience knowledge. This knowledge cultivation involves personalization, customization, and a comprehensive customer experience (Customer Experience 360), which supports informed decision-making in demand forecasting, market segmentation, product offering, product categorization, and business positioning. Ultimately, the optimized fintech ecosystem enhances customer satisfaction, growth, and productivity by improving the quality of services and products.

4.4.2. Answer to the questions

RQ1: What are the main and effective components in providing the knowledge management of the customer experience model through machine learning?

Based on the tested conceptual model, SEM, and the APO-CEM model, the main and effective components in providing the customer experience management model include:

(15) Vision and Mission: The foundational goals and direction of the organization.

- Customer Perceptions: This includes service speed, service quality, performance speed, brand trust, and innovation.
- Applying KM Management Components: This involves identifying, creating, sharing, storing, and applying knowledge.
- Applying AI/ML Technology: This encompasses learning, business intelligence, service innovation, and product innovation.
- Customer Knowledge Cultivation: This involves Knowledge Personalization, Knowledge Customization, and Customer Experience 360.
- Consequences: The outcomes include profitability, customer satisfaction, and customer loyalty.
- Fintech Knowledge Core: The central knowledge base specific to the fintech industry.

RQ2: Which knowledge management model is the closest to developing the knowledge management of customer experience model?

Previous studies have demonstrated that the knowledge management model based on the APO framework is particularly effective, ensuring that no critical element is overlooked during implementation (Cahyaningsih et al., 2017). Additionally, the APO framework serves as a tool for evaluating knowledge management, offering insights into areas where the organization should focus its knowledge management initiatives and innovations (Khajouei et al., 2017).

RQ3: Is machine learning a suitable tool for interpreting customer experience perceptions based on knowledge management models?

By utilizing sentiment analysis techniques and a combined method of machine learning with a word-based approach, customer perceptions expressed in comment texts were categorized and coded using sentiment analysis algorithms. Subsequently, a decision tree was constructed through machine learning. Additionally, previous studies confirm that knowledge management and the decision tree algorithm effectively classify knowledge quality. They also highlight the advantages of using machine learning for the development of knowledge management from both theoretical and practical perspectives (Kaun et al., 2021).

5. Discussion and conclusion

This research aimed to present a knowledge management of customer experience model through machine learning. The paper's main contribution is the development of the APO-CEM model in the fintech domain. The study provides a comprehensive framework for integrating customer experience and knowledge management through artificial intelligence. The research confirms a substantial need to develop a knowledge management of customer experience model in fintech. This finding underscores the necessity for a robust theoretical framework in knowledge management of customer experience. The study highlights that existing models are insufficient in addressing the dynamic needs of fintech customers. The proposed customer experience management model based on the knowledge management framework introduces a significant innovation in fintech. This model incorporates customer perceptions such as innovation, performance quality, service quality, service speed, and brand trust, applying knowledge management components through artificial intelligence. The model's application of knowledge personalization, customization, and a 360-degree view of customer experience has been rigorously tested and validated. This comprehensive approach provides a more nuanced understanding of customer interactions and their impact on overall customer experience. The study demonstrates that artificial intelligence can enhance conceptual knowledge management tools by incorporating social perceptions into the knowledge process. The research examines AI's potential to support learning and knowledge development in three key areas: the necessity for learning, the learning system for interpreting customer perceptions, and the evolution of learning towards human-level intelligence. Integrating AI into knowledge management processes shows promise in advancing customer experience management. The research reveals that machine learning has significant potential when implemented as a coherent knowledge-based system. Specifically, machine learning improves comprehensive knowledge management models like APO and enhances new areas, such as text coding of customer opinions and experiences for decision tree applications. Enhancing decision tree accuracy through hyperparameter tuning is a key innovation, contributing to more precise and actionable insights.

Future research could explore using Bayesian networks and mixed-methods approaches, incorporating variables such as communication capital, intellectual values, and technology utilization. Further research could focus on developing a cultivation theory for customer experience knowledge using grounded theory methods and assessing its effectiveness in the fintech ecosystem. It is recommended that the APO-CEM model be specifically used to handle problems like assessing customer experience data in fintech firms and optimizing customer interactions to strengthen the suggestions. For example, organizations could use this model to personalize services and predict customer behavior. In conclusion, the APO-CEM model offers the potential for fintech organizations to enhance customer experiences and improve strategic decision-making. Integrating machine learning into knowledge management frameworks represents a critical advancement in understanding and optimizing customer interactions.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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