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Identification of the Critical Enablers for Perishable Food Supply Chain Using Deterministic Assessment Models

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Abstract: Today's perishable food supply chains must be resilient to handle volatile demands, environmental restrictions, and disruptions in order to meet customers' requirements. The enablers of the perishable food supply chain have not yet been explored. In this paper, a bibliometric systematic literature review has been conducted to identify the articles related to the perishable food supply chain. Next, with these identified articles, a map is created with bibliographic data using Vosviewer network visualization software, and then the enablers were identified by conducting keyword co-occurrence analysis. Later, a total interpretive structural modeling (TISM) is employed to analyze the interrelationships among enablers and then determine each enabler's hierarchies, further representing them in a diagraph. Finally, the identified enablers are classified using cross-impact matrix multiplication applied to classification (MICMAC) analysis, and the graph is plotted. The results obtained from the deterministic assessment model provide the critical enablers for the perishable food supply chain. The obtained critical enablers and their hierarchies provide valuable insights for researchers in the context of perishable food supply chain for further study.

Keywords: total interpretive structural modeling (TISM); Vosviewer; perishable products; enablers; cross impact matrix multiplication applied to classification (MICMAC)

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1. Introduction

The handling of perishable products in supply chains is complex; these are distinguished from other products in terms of fundamental differences, such as shelf life, cold storage, and deterioration rate, from upstream to downstream in the perishable food supply chain (PFSC). Many nations' citizens are inclined toward healthy diets, raising the demand for perishable products such as fresh fruits, vegetables, and milk. These products are critical to handle in real-time, and managing critical parameters such as cost, quality, and freshness enhances the decision-making process of PFSC management. However, continuous monitoring is necessary throughout the supply chain (SC) to maintain these parameters at desired levels [1].

Variations in demand, stringent environmental regulations, and catastrophic disruptions make handling current PFSCs very complex. Recent technological advancements in PFSCs have helped in the management of the above-mentioned difficulties; in turn, these technologies may further help improve the enablers associated with inventory control, transportation, and sustainability aspects. The digitalization of PFSC helps in data sharing and monitoring the process and products. For example, radio frequency identification (RFID) has been most significant for food quality, freshness-keeping monitoring, and maintaining delivery times based on environmental conditions [2]. Inventory management controls the quantity and quality of the perishable products within their limited shelf life. An appropriate transportation process helps control variables such as vehicle routing, fuel consumption, and cost and makes the product reach the end customer before its deterioration. Hence, the identification of enablers is significant during PFSC. The critical enablers are identified using a deterministic assessment model. Additionally, it is necessary to find the trade-off between profits and sustainability in present times because of the rise in the effects of global warming [3].

The current study aims to identify the significant enablers of PFSC by conducting a systematic literature review. The study's primary objectives are as follows:

1. Identifying the important enablers in the perishable food supply chain;
2. Finding the interrelationships among enablers, hierarchies of each enabler, and most driving and dependency enablers in PFSC;
3. The classification of the enablers based on driving and dependency values using MICMAC analysis [4,5].

The remainder of this paper has been organized as mentioned below. Section 2 describes the significance of enablers' literature related to the current study and identification of enablers using Vosviewer network visualization software. Sections 3 and 4 elaborate on the levels of each enabler using the TISM–MICMAC methodology, followed by the findings and discussion in Section 5. Finally, implications and conclusions are presented in Sections 6 and 7, respectively.

2. Literature Review

Perishable food supply chain (PFSC) management is a challenging domain due to its unpredictable changes and rigorous food safety, quality, and sustainability requirements across the SC [6]. In order to maintain the mentioned requirements and make an efficient cold chain (CC) system, it is necessary to maintain perishable food within the desired temperature to maintain consumer confidence [7]. This literature review is carried out to investigate the enablers of CC as a major context. We conducted a systematic review (bibliometric analysis) using a SCOPUS search and then analyzed the results with Vosviewer keyword co-occurrence analysis (VKCA) (www.vosviewer.com, accessed on 17 December 2021). This approach has been effectively applied by Ali and Golgeci (2019) [8], and they stated that "VKCA helps to objectively and algorithmically identify and aggregate the important phrases into discrete clusters, reflecting the primary study themes and paths of future research in the subject". The SCOPUS database has been used for the literature search since it is the largest abstract and citation database [9]. The bibliometric data were collected using the search string: "supply chain reconfigurability" OR "sustainable supply chain" OR "cold supply chain" OR "digital supply chain" OR "industry 4.0" OR "digital twin" OR "supply chain resilience". While conducting the search, papers were selected using the search alert, refined by the document type of article and review articles, with the years restricted from 2000 to 2020, and the language as English, and the subject areas considered were engineering, computer science, decision science, and business management and accounting. The irrelevant articles were filtered out, and finally, the fifty-four most relevant references were considered for further analysis. Later, the enablers were identified using VKCA, and their interrelationships were found. The hierarchy of each enabler was found using the TISM-MICMAC approach. The following sections explain the literature.

2.1. Identification of PFSC Enablers

This section identifies the PFSC enablers with the help of VKCA. The bibliometric data of 54 selected articles were collected as stated above, and a bibliographic map was created using VKCA. The keyword co-occurrence analysis was conducted with a minimum of 2 keywords, and seven clusters were formed. The bibliographic map of seven clusters is shown in Figure 1.

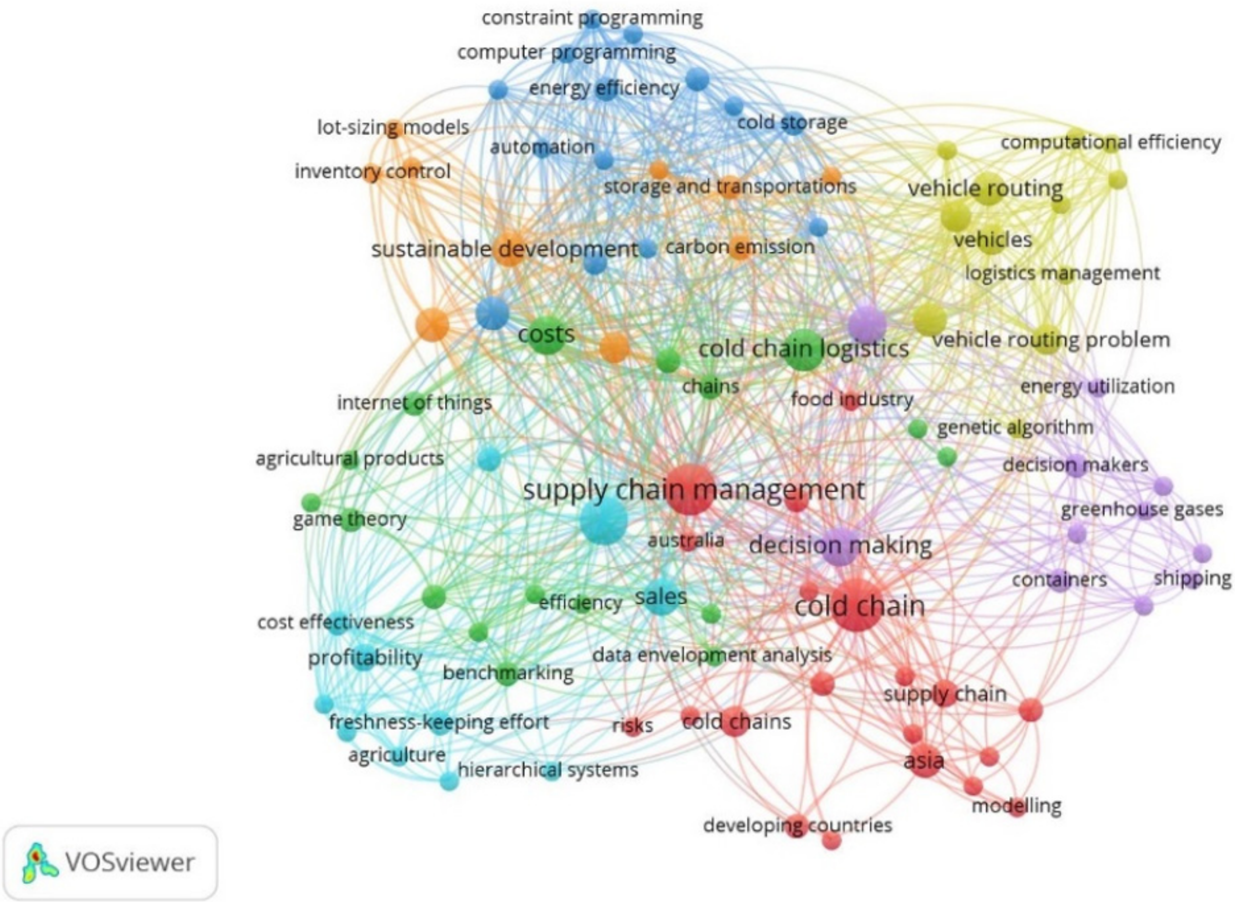

Figure 1. Vosviewer keyword co-occurrence analysis (Bibliographic map).

After VKCA, four themes were identified from seven clusters, viz., digitalization (green), inventory (red and orange), transportation (blue, pink, and cyan), and sustainability (purple). Fifteen enablers were identified from the four themes. In Table 1, the details of the fifteen enablers of PFSC has been provided.

2.1.1. Perishable Supply Chain Related to RFID and IoT Technologies (Digitalization)

Durán Peña et al. (2021) [10] implemented RFID technology for the PFSC to capture the real-time demand signal; this helps to identify the most essential elements that affect the bullwhip effect. In addition to RFID tags with various types of sensors, a ubiquitous cold-chain-logistics-based intelligent-risk-management framework has been suggested by Kim et al. (2016) [2]. It is challenging to maintain different temperatures for different types of perishable goods in the same container. Laniel et al. (2011) [11] tested a container loaded with frozen food at two different frequencies with the refrigeration unit running at −25 degrees Celsius and concluded that the 433 MHz RFID technology appeared to be acceptable for monitoring the temperature of frozen bread inside a sea container.

The recent industrial revolution emphasizes the deployment of the latest technologies in various domains for efficient and effective planning and control. PFSC and the Cold Supply Chain (CSC) have provided the greatest opportunities to adopt the recent technology, i.e., IoT, for their benefits. Bogataj et al. (2017) [12] evaluated the changes in net present value (NPV) from the expected shelf-life changes, which are enabled by IoT infrastructures such as devices that track temperature, humidity, and gas concentrations. Sun et al. (2019) [13] provided a scientific basis for organizations engaged in the CC operation of fresh agricultural products to invest in IoT. Blockchain technology is one of the revolutionary technologies that evolved from Industry 4.0. This technology brings transparency and security to disciplines where it has been adopted. The supply chain has the greatest potential to use its resources. However, one of the works conducted by Sunny et al. (2020) [14] gave an outline of how IoT and smart contract technologies are enhancing blockchain's possibilities. In addition, they demonstrated how transparency could be achieved with blockchain technology with a proof of concept for a CC scenario using Microsoft Azure Blockchain Workbench.

Table 1. Fifteen enablers from Vosviewer keyword co-occurrence analysis.

Theme	Enablers Number	Name of the Enabler
Digitalization	1	Radiofrequency identification (RFID)
	2	Internet of things (IoT)
Inventory	3	Shelf life (SL)
	4	Cold storage (CS)
	5	Inventory control (IC)
	6	Decision making (DM)
Transportation	7	Third-party logistics (3PL)
	8	Vehicle routing (VR)
	9	Unit capacity (UC)
	10	Fuel consumption (FC)
	11	Freshness keeping (FK)
	12	Cost–benefit analysis (CBA)
Sustainability	13	Global warming (GW)
	14	Carbon emission (CE)
	15	Energy utilization (EU)

The enablers mentioned above were discussed in detail in the following subsections according to their themes.

Faisal Rasool et al. (2021) [15] highlighted the need for qualitative performance measuring metrics for Digital Supply Chain (DSC) and identified the metrics of internal and financial perspectives, which have attracted the most attention. In contrast, growth and learning perspectives received the least attention. Through mixed review methodologies, Sitsofe Kwame Yevu et al. (2021) [16] presented state-of-the-art research on DSC and procurement technologies in the built environment, revealing knowledge areas that are needed to promote digitalization in the building SC.

2.1.2. Perishable Supply Chain Related to Shelf Life, Cold Storage, Inventory Control, and Decision Making (Inventory)

In PFSC, opportunity cost, shelf life restriction, and product transportation units are used to determine value degradation. Singh et al. (2018) [17] suggested a CC location–allocation configuration modeling approach for shippers and customers that includes value deterioration and coordination using big data approximation. The proposed model is addressed as a mixed-integer linear programming (MILP) problem and solved using a CPLEX solver. Moreover, Chen et al. (2018) [9] offered a model for reducing the cost of consolidation and the loss of product value due to a shorter shelf-life of fresh agricultural products to develop criteria for categorizing their storage needs. Hsiao (2018) [18] in the Vehicle Routing Problem (VRP) with time periods considered the properties of many perishable items, continued quality decrease, and optimal temperature settings during the transportation and used a genetic algorithm (GA) to solve the VRP with time windows.

However, the benchmarking framework developed by Joshi et al. (2011) [19] identifies the strengths and weaknesses of a company's CC performance for perishable products and then prioritizes the possible improvements. The proposed framework helps decision-makers to better comprehend the complicated relationships between CC performance factors. According to the SC structure, Aiello et al. (2012) [20] developed a methodology to evaluate the performance of a CC in terms of predicted product quality at the retail store and estimated the expected proportion of perished products. Later, Chaudhuri et al. (2018) [21] provided an overview of data capture, types of technologies used for data collection, sharing of information, and decision making. Based on findings from 38 publications, the data across the CC can aid various types of perishable foods.

2.1.3. Perishable Supply Chain Related to Third Party Logistics (3PL), Vehicle Routing, Unit Capacity, Fuel Consumptions, Cost–Benefit Analysis, and Freshness Keeping (Transportation)

3PL plays a critical role in maintaining the quality of perishable products. Based on ten different criteria, Singh et al. (2018) [22] presented a hybrid model (Fuzzy AHP and TOPSIS) for selecting 3PL that can handle the perishable products based on an emphasis on automation and innovation in the CC processes. Zhang et al. (2020) [1] analyzed the effects of different time windows for the retailer and other cost-related factors on the choice of legitimacy, food quality, and pollutant emissions of distribution firms in urban areas. Their study suggests that the government time frames would increase distribution costs and pollutant emissions while improving food safety. Awad et al. (2020) [23] reviewed food SC products' distribution work and suggested a dynamic vehicle modeling and routing while considering product quality and environmental impacts. Hsiao et al. (2018) [18] analyzed a VRP with time windows for fruit-and-vegetable co-distribution using GA.

However, Meneghetti and Ceschia (2020) [24] designed a problem regarding refrigerated routing where multiple deliveries of frozen food were made from a central facility to customers, with an objective of selecting the route for refrigeration that gives the lowest fuel consumption. Cai et al. (2010) [25] developed an optimization model for decision parameters (such as the damage during transportation and cost associated with the freshness-keeping process) in perishable goods' SC. Their computational studies have assessed the results of freshness-keeping efforts along with profit–loss trade-offs. Moreover, Wang et al. (2020) [3] looked into a fresh product SC involving cost-based freshness-keeping efforts by formulating a function with linear demand. Their studies reveal better greenness levels compared to a decentralized model. Furthermore, Song and Wu (2022) [26] proposed MILP for location inventory routing problem for perishable goods. The CPLEX solver is used to minimize the total cost of the SC involved.

2.1.4. Perishable Food Supply Chain Related to Global Warming, Carbon Emissions, and Energy Utilization (Sustainability)

Perishable products require cold storage in SC to maintain freshness due to their limited shelf life. Ma et al. (2020) [27] studied a coordination method in a three-echelon SC considering the freshness-keeping effort by 3PL service providers, where SC decisions on carbon trading mechanisms were investigated under two alternative systems. The findings demonstrated that total carbon emissions are reduced with an increase in the eco-friendliness effort. Leng et al. (2020) [28] proposed a multi-objective hyper-heuristic approach for a real problem of location-routing concerning low-carbon CC, involving minimizing the fuel usage prices, product freshness, and carbon emissions. Sepehri (2021) [29] integrated environmental regulations and credit risk for the inventory models by developing an algorithm to find the trade-off value for green technology investment.

Soysal et al. (2015) [30] used a model to simulate a real-world SC in which a distribution center delivers fresh tomatoes to stores, and key performance indicators were provided to optimize various metrics (such as total cost, carbon emissions). Bortolini et al. (2016) [31] examined the distribution of different types of fruits and vegetables grown by Italian farmers by utilizing three different means of transportation, and the food distribution planner was a proposed system that efficiently controlled product perishability while limiting CO_2 emissions. Solina and Mirabelli (2021) [32] presented an optimization model for the integrated distribution and production activity scheduling that considers perishability and changeover times to reduce expenses and energy consumption. The literature review summary for enablers of PFSC is provided in Table 2. The numbers 1 to 15 (Table 1) are the enablers obtained from Section 2.1.

Table 2. Summary of literature review for enablers of PFSC.

	RFID	IoT	SL	CS	IC	DM	3PL	VR	UC	FC	FK	CBA	GW	CE	EU
Authors/Enablers	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
Zhang et al. (2020) [1]								✓							
Kim et al. (2016) [2]	✓														
Wang et al. (2020) [6]											✓				
Laniel et al. (2011) [11]	✓														
Sun et al. (2020) [13]		✓													
Sunny et al. (2020) [14]		✓													
Singh et al. (2018) [17]			✓												
Joshi et al. (2011) [19]						✓									
Aiello et al. (2012) [20]			✓												
Singh et al. (2018) [22]							✓								
Ma et al. (2020) [27]						✓					✓	✓		✓	
Leng et al. (2020) [28]										✓				✓	
Chen et al. (2019) [33]						✓		✓		✓					
Bozorgi et al. (2014) [34]				✓	✓				✓					✓	
Stellingwerf et al. (2018) [35]				✓				✓		✓					
Wei et al. (2019) [36]				✓				✓							
Song et al. (2020) [37]								✓							✓
Saif and Elhedhli (2016) [38]													✓		✓
Current study	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

2.2. Literature Review for TISM–MICMAC Approach

In this section, the TISM–MICMAC methodology is identified for different scenarios from the literature to determine the interrelationship between the enablers, hierarchies, and critical enablers. A summary of the TISM–MICMAC methodology for different problems is presented in Table 3.

Table 3. Summary of literature review for TISM–MICMAC methodology.

Contributors	Problem	Method Used	Features
Amir et al. (2021) [39]	Identification of barriers to Lithium-ion batteries for electric vehicles in reverse logistics	TISM–MICMAC	Eight enablers were evaluated, and the most dominant barrier categories were found.
Bathrinath et al. (2021) [40]	Identifying the most important activity in the heat treatment process	TISM–MICMAC	Out of eighteen activities, three were identified as the most important activities: material handling, painting, and quenching.
Rahul Sindhwani et al. (2016) [41]	Identification of enablers for modeling of the agile manufacturing system	TISM–MICMAC	With TISM and MICMAC analysis, the current model analyzes the effect of enablers, mutual relationships, and the correlation between enablers.
Meena et al. (2020) [42]	Identification and evaluation of several growth-accelerating variables in the Indian automobile sector	TISM–MICMAC	Evaluated eight enablers for the growth of the automobile industry in India and highlighted the most important ones for the Indian automotive sector.
Current study	Identification of enablers and the levels of each enabler in PFSC	TISM–MICMAC	Fifteen enablers have been identified and classified in terms of the level of each enabler and type for PFSC

2.3. Summary of the Literature

In the current study, we extended the previous efforts by identifying the enablers of PFSC. To our knowledge, no study has examined the critical enablers in this area. Moreover, depending on the situation (such as demand uncertainty, pandemics, and environmental conditions), the identified enablers in PFSC have been helpful in the decision-making process [2,33–35,43]. TISM–MICMAC approach was effective for finding the interrelationships among enablers in various domains. There is an essential need for enablers for PFSC in the current situation.

3. Methodology

In this paper, the TISM–MICMAC approach has been applied to determine the relationship between enablers and their hierarchies. Additionally, this approach helps to find the critical enablers.

Initially, we identified the PFSC enablers using VKCA from the systematic literature review. Next, using the TISM approach, the driving (D_R) and dependency (D_C) values were calculated for each enabler and portrayed in the diagraph. Finally, the fifteen identified enablers were classified using MICMAC analysis based on the D_R and D_C. The proposed method is described in Figure 2.

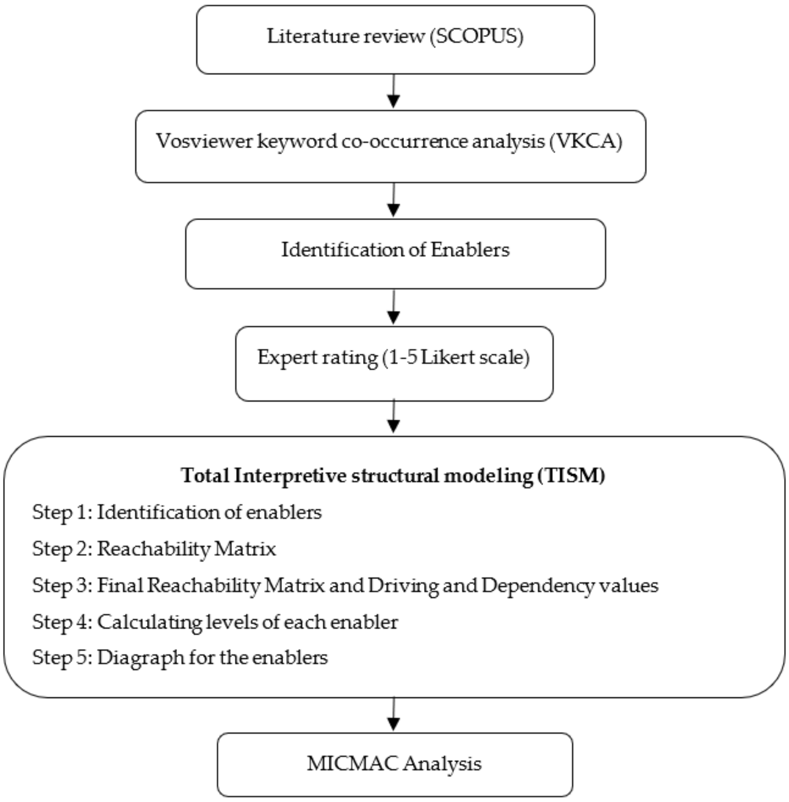

Figure 2. Proposed method.

3.1. Total Interpretative Structural Modeling (TISM)

This section describes the steps involved in the TISM approach. TISM has been adopted in this paper to establish the relations between enablers logically using a conventional qualitative modeling technique. The TISM is a new qualitative modeling approach that is based on ISM [36]. The TISM approach has been used to identify the interrelationships between enablers and the levels of each enabler and critical enablers for different scenarios [44–46]. The following subsection explains the steps involved in TISM.

3.1.1. Step 1: Identification of Enablers

The first step in the TISM process is to identify the enablers for the PFSC. Fifteen enablers were identified by VKCA using Vosviewer network visualization software through systematic literature (Bibliometric analysis), as mentioned in Section 2.1. All fifteen of the enablers are listed in Table 1.

3.1.2. Step 2: Initial Reachability Matrix (Representation of Enablers in Matrix Form)

The second step aims to achieve a correlation matrix among the enablers for pair-wise comparison (initial reachability matrix). An online survey (questionnaire) was conducted, and ratings were taken from experts to find the interrelationships among enablers. The experts considered in this study were from three areas: academics, digital marketing experts, and perishable food-management experts. Experts utilized a Likert scale ranging from 1 to 5 to quantify the interdependencies of enablers with each other, as shown in Table 4.

Table 4. Quantification of the interdependencies of enablers (Likert 5-point scale).

Category	Rating
Very strong	5
Strong	4
Medium	3
Weak	2
Very weak	1

As per the experts' opinion, if there is an interrelationship among the enablers, the answer is Yes (Y), and an additional interpretation is required. Otherwise, the answer is considered No (N). The response rate was around 68 percent, which is sufficient for this type of survey [42]. The obtained responses from experts are represented in a matrix form, considering that Y is "1" and N is "0". Table 5 provides the responses collected from various experts.

Table 5. Initial reachability matrix (IRM).

Enabler Number	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	1	1	0	1	1	1	0	0	0	0	0	0	0	0	0
2	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0
3	1	0	1	0	0	0	1	1	0	0	1	1	0	0	0
4	0	1	0	1	0	0	0	0	0	0	0	1	1	0	1
5	0	1	1	1	1	1	1	1	0	0	0	0	1	0	1
6	0	0	0	1	1	1	0	0	0	0	0	1	1	0	0
7	0	0	0	0	1	1	1	1	0	0	0	0	0	0	0
8	0	0	1	0	1	1	1	1	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0	0	1	1	0	1	1	1
11	0	0	0	0	0	0	0	0	0	1	1	0	0	1	0
12	0	0	0	1	1	1	0	0	0	0	0	1	0	0	1
13	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0
14	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1
15	0	0	0	1	0	0	0	0	0	1	0	0	1	1	1

3.1.3. Step 3: Final Reachability Matrix and Driving (D_R) and Dependence (D_C) Values

After obtaining the initial reachability matrix from the experts' opinion, the transitivity rule of the matrix was checked (if E4–E7, E7–E10, then E4–E10). Each transitive connection was updated with 1* in the respective cell of the matrix. Table 6 shows the updated matrix with all the transitivity connections. The D_R and D_C values were calculated from the final reachability matrix by adding row and column values, respectively. The D_R and D_C values are shown in the last row and last column of Table 6.

Table 6. Final reachability matrix and D_R and D_C Values.

Enablers	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	$\mathbf{D_R}$
1	1	1	1*	1	1	1	1*	1*	0	0	0	1*	1*	0	1*	11
2	1	1	0	1	1*	1*	0	0	0	0	0	1*	1*	0	1*	8
3	1	1*	1	1*	1*	1*	1	1	0	1*	1	1	0	1*	1*	13
4	1*	1	0	1	1*	1*	0	0	0	1*	0	1	1	1*	1	10
5	1*	1	1	1	1	1	1	1	0	1*	1*	1*	1	1*	1	14
6	0	1*	1*	1	1	1	1*	1*	0	0	0	1	1	1*	1*	11
7	0	1*	1*	1*	1	1	1	1	0	0	0	1*	1*	0	1*	10
8	1*	1*	1	1*	1	1	1	1	0	0	1*	1*	1*	0	1*	12
9	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1
10	0	0	0	1*	0	0	0	0	0	1	1	0	1	1	1	6
11	0	0	0	0	0	0	0	0	0	1	1	0	1*	1	1*	5
12	0	1*	1*	1	1	1	1*	1*	0	1*	0	1	1*	1*	1	12
13	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1*	3
14	0	0	0	1*	0	0	0	0	0	1*	0	0	1	1	1	5
15	0	1*	0	1	0	0	0	0	0	1	1*	1*	1	1	1	8
D_C	6	10	7	12	9	9	7	7	1	8	6	10	13	10	14	

3.1.4. Step 4: Levels of Each Enabler (Hierarchy)

In this step, we identified each level for the enablers mentioned above. Thus, the final reachability matrix (FRM) was used to calculate the reachability set (RS) and antecedent set (AS) for each enabler. The RS includes the enabler itself and the enablers affected by it. The AS includes the enabler itself and the ones that affect the enabler. Later, the intersection set is calculated from the achieved RS and AS [21]. The enablers common to both the reachability and intersection sets are considered for the first level of the hierarchy in TISM. After completing the first level of enablers, they are removed to determine the next level of enablers. The above procedure is repeated until all the enablers are ranked. Table 7 illustrates the hierarchies of each enabler.

Table 7. Hierarchy levels of each enabler.

Enabler	**Reachability Set (RS)**	**Antecedent Set (AS)**	**Intersection Set**	**Level**
		Iteration 1—Level I		
1	1,2,3,4,5,6,7,8,12,13,15	1,2,3,4,5,8	1,2,3,4,5,8	
2	1,2,4,5,6,12,13,15	1,2,3,4,5,6,7,8,12,15	1,2,4,5,6,12,15	
3	1,2,3,4,5,6,7,8,10,11,12,14,15	1,3,5,6,7,8,12	1,3,5,6,7,8,12	
4	1,2,4,5,6,10,12,13,14,15	1,2,3,4,5,6,7,8,10,12,14,15	1,2,4,5,6,10,12,14,15	
5	1,2,3,4,5,6,7,8,10,11,12,14	1,2,3,4,5,6,7,8,12	1,2,3,4,5,6,7,8,12	
6	2,3,4,5,6,7,8,12,14	1,2,3,4,5,6,7,8,12	2,3,4,5,6,7,8,12	

Table 7. *Cont.*

Enabler	Reachability Set (RS)	Antecedent Set (AS)	Intersection Set	Level
7	2,3,4,5,6,7,8,12	1,3,5,6,7,8,12	3,5,6,7,8,12	
8	1,2,3,4,5,6,7,8,11,12	1,3,5,6,7,8,12	1,3,5,6,7,8,12	
9	9	9	9	I
10	4,10,11,13,14,15	3,4,5,10,11,12,14	4,10,11,14,15	
11	10,11,13,14,15	3,5,8,10,11,15	10,11,15	
12	2,3,4,5,6,7,8,10,12,13,14,15	1,2,3,4,5,6,7,8,12,15	2,3,4,5,6,7,8,12,15	
13	13,14,15	1,2,4,5,6,7,8,10,11,12,13,14,15	13,14,15	I
14	2,10,13,14,15	3,4,5,6,10,11,12,13,14,15	10,13,14,15	
15	2,4,10,11,12,13,14,15	1,2,3,4,5,6,7,8,10,11,12,13,14,15	2,4,10,11,12,13,14,15	I
		Iteration 2—Level II		
1	1,2,3,4,5,6,7,8,12,	1,2,3,4,5,8	1,2,3,4,5,8	
2	1,2,4,5,6,12	1,2,3,4,5,6,7,8,12	1,2,4,5,6,12	II
3	1,2,3,4,5,6,7,8,10,11,12,14	1,3,5,6,7,8,12	1,3,5,6,7,8,12	
4	1,2,4,5,6,10,12,14	1,2,3,4,5,6,7,8,10,12,14	1,2,4,5,6,10,12,14	II
5	1,2,3,4,5,6,7,8,10,11,12,14	1,2,3,4,5,6,7,8,12	1,2,3,4,5,6,7,8,12	
6	2,3,4,5,6,7,8,12,14	1,2,3,4,5,6,7,8,12	2,3,4,5,6,7,8,12	
7	2,3,4,5,6,7,8,12	1,3,5,6,7,8,12	3,5,6,7,8,12	
8	1,2,3,4,5,6,7,8,11,12	1,3,5,6,7,8,12	1,3,5,6,7,8,12	
10	4,10,11,14	3,4,5,10,11,12,14	4,10,11,14	II
11	10,11,14	3,5,8,10,11	10,11	
12	2,3,4,5,6,7,8,10,12,14	1,2,3,4,5,6,7,8,12	2,3,4,5,6,7,8,12	
14	2,10,14	3,4,5,6,10,11,12,14	10,14	
		Iteration 3—Level III		
1	1,3,5,6,7,8,12	1,3,5,8	1,3,5,8	
3	1,3,5,6,7,8,11,12,14	1,3,5,6,7,8,12	1,3,5,6,7,8,12	
5	1,3,5,6,7,8,11,12,14	1,3,5,6,7,8,12	1,3,5,6,7,8,12	
6	3,5,6,7,8,12,14	1,3,5,6,7,8,12	3,5,6,7,8,12	
7	3,5,6,7,8,12	1,3,5,6,7,8,12	3,5,6,7,8,12	III
8	1,3,5,6,7,8,11,12	1,3,5,6,7,8,12	1,3,5,6,7,8,12	
11	11,14	3,5,8,11	11	
12	3,5,6,7,8,12,14	1,3,5,6,7,8,12	3,5,6,7,8,12	
14	14	3,5,6,11,12,14	14	III
		Iteration 4—Level IV		
1	1,3,5,6,8,12	1,3,5,8	1,3,5,8	
3	1,3,5,6,8,11,12	1,3,5,6,8,12	1,3,5,6,8,12	
5	1,3,5,6,8,11,12	1,3,5,6,8,12	1,3,5,6,8,12	
6	3,5,6,8,12	1,3,5,6,8,12	3,5,6,8,12	IV
8	1,3,5,6,8,11,12	1,3,5,6,8,12	1,3,5,6,8,12	
11	11	3,5,8,11	11	IV
12	3,5,6,8,12	1,3,5,6,8,12	3,5,6,8,12	IV
		Iteration 5—Level V		
1	1,3,5,8	1,3,5,8	1,3,5,8	V
3	1,3,5,8	1,3,5,8	1,3,5,8	V
5	1,3,5,8	1,3,5,8	1,3,5,8	V
8	1,3,5,8	1,3,5,8	1,3,5,8	V

3.1.5. Step 5: Diagraph for the Enablers

In this step, a diagraph was created to represent the enablers. The diagraph was plotted based on the attained levels and relationships among the enablers, and it consisted of direct and transitivity links from the initial and final reachability matrices (from steps 1 and 2). The diagraph is shown in Figure 3.

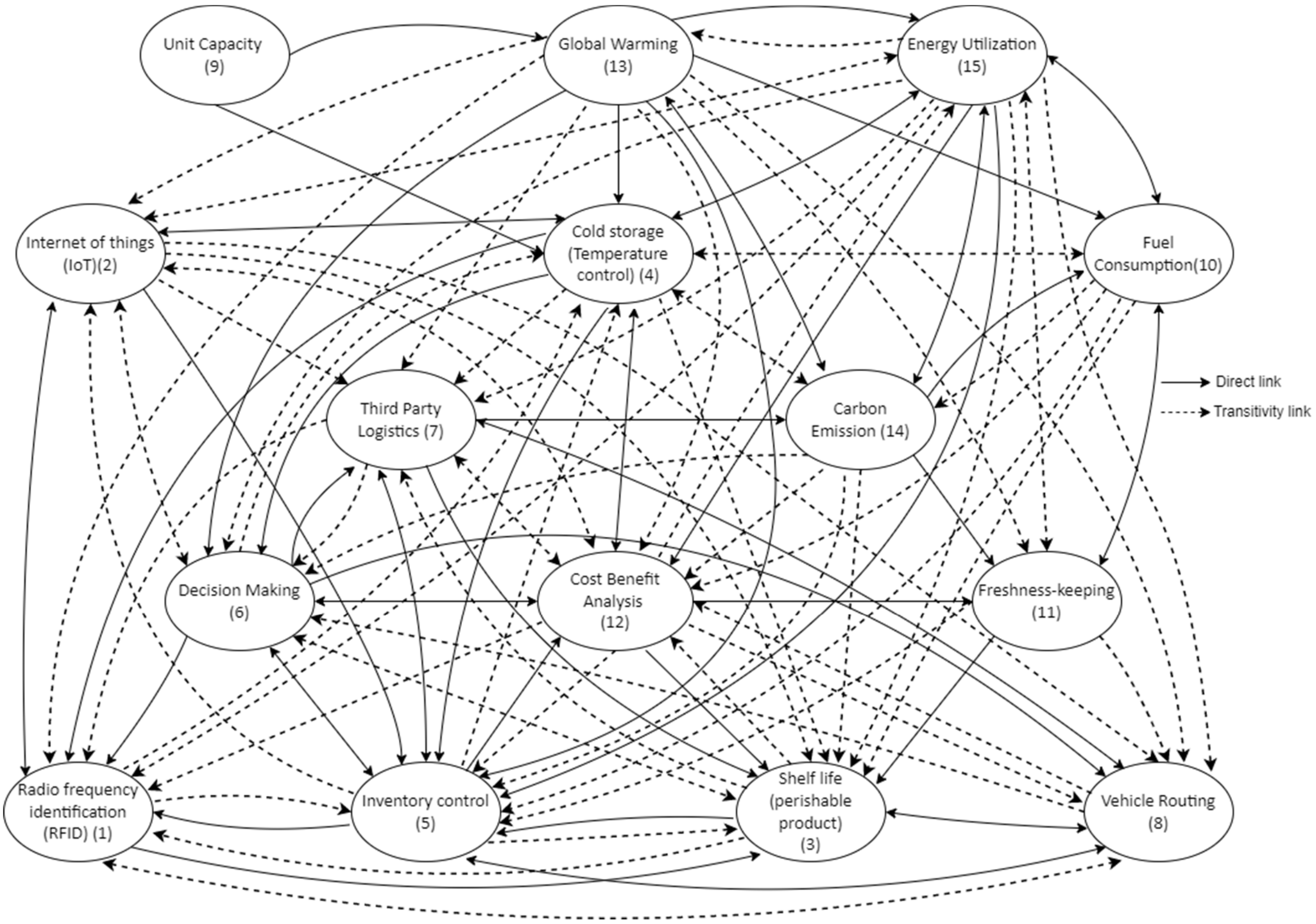

Figure 3. Diagram of perishable food supply chain enablers.

4. MICMAC Analysis for Enabler's Classification

MICMAC analysis was used to identify and categorize the enablers of PFSC using the driving and dependency values obtained from TISM [40–42]. The primary aim of this section is to identify the D_R and D_C values. The driving values were calculated by adding each row of the enablers using the FRM. Similarly, the dependency values were calculated by adding each column of the enablers. Table 6 shows the results thus obtained. After these values were calculated, they were categorized into four types: autonomous enablers, driving enablers, independent, and enablers linkage enablers [2].

- Autonomous enablers: These enablers are represented in the first quadrant (bottom left corner). These enablers have low driving and dependence values since they do not have enough relationships with others.
- Driving enablers: These are also called independent enablers. Represented in the second quadrant (top left corner), they have a high driving value and low dependency values. Therefore, they are categorized as the most influential enablers of the PFSC.
- Linkage enablers: These enablers are represented in the third quadrant (top right corner) and have high driving and dependency values. Linkage enablers have a lot of command over the PFSC, but they also rely on other factors.
- Dependent enablers: These enablers are in the fourth quadrant (bottom right corner) and have high dependency and low driving values since other enablers affect them.

Figure 4 illustrates the enablers classification using the MICMAC analysis. The enablers in the upper half of Figure 4 can be labeled as essential enablers as these play a critical role in the PFSC. From Figure 4, it is evident that most of the enablers are classified as driving and linkage enablers.

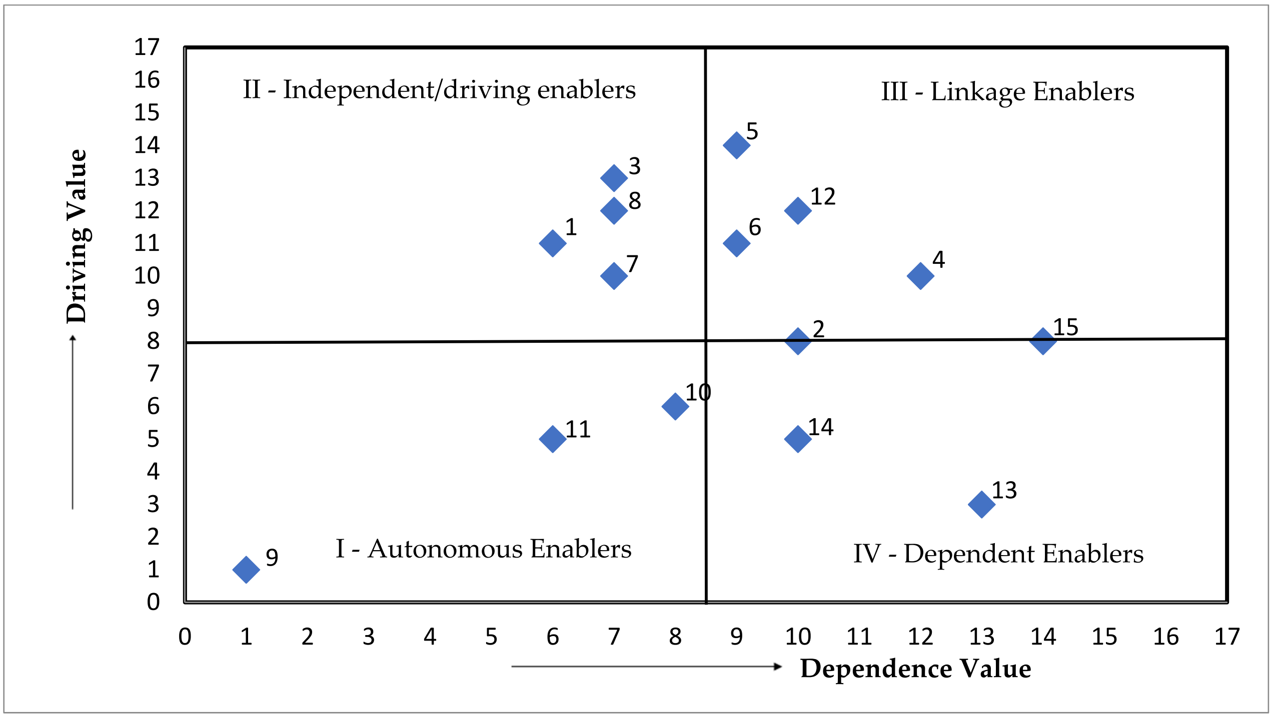

Figure 4. Enabler's classification utilizing MICMAC analysis.

5. Findings and Discussion

As mentioned above, there are a number of enablers for PFSC that must be considered. This study uses an integrated strategy of TISM and MICMAC methodologies to identify and analyze these enablers. There is a limited amount of literature on PFSC enablers, as discussed in Section 2. First, the relevant enablers for PFSC were identified using Vosviewer. In addition, an integrated approach using the TISM methodology was applied to find hierarchies by considering experts' ratings of them. Finally, enablers were classified into four types using MICMAC analysis based on the D_R and D_C values from the final reachability matrix. A detailed discussion of the critical relationships between enablers is presented below.

1. Radiofrequency identification (RFID): RFID is seen in level V of the TISM hierarchy. From MICMAC analysis, this enabler is considered one among the most driving ones and falls under the second quadrant due to its high driving and low dependency values. RFID was most significant for food quality, freshness-keeping, and maintaining the delivery times based on environmental conditions [2]. Perishable food products deteriorate due to temperature fluctuations during transportation. Hence, RFID is helpful to monitor temperature settings [10].
2. Internet of things (IoT): An IoT enabler has been in level II of the TISM hierarchy, and from MICMAC analysis, it is a type 3 linkage enabler. These enablers are unique in that any action taken against them will influence other enablers. IoT is a smart device technology that has been helpful in finding the ambient conditions of PFSC, such as temperature and humidity [11].
3. Shelf life: Shelf life lies in level V of the TISM hierarchy, and as shown by MICMAC analysis, this enabler is considered one of the most driving enablers. Due to its high driving and low dependency values, it falls in the second quadrant. The shelf life and quality of the perishable product are based on deterioration. Hence, perishable products must be delivered to the target before shelf life expiry [8,16,17].
4. Cold storage: Cold storage is present in the fourth level of the TISM hierarchy and is a type three linkage enabler according to MICMAC analysis. Vehicles' cold storage plays a significant role in maintaining the freshness and reducing the deterioration of

perishable products [36]. Cold storage affects the product's shelf life, which in turn affects other enablers of PFSC.

5. Inventory control: Inventory control belongs to level I of the TISM hierarchy, and according to MICMAC analysis, it is classified as a linkage enabler due to its dependency and driving value. Inventory must be maintained based on the demand for the product. Since these products have a shorter shelf life, there are high chances of product spoilage and losses, leading to a situation where consumer demand may not be fulfilled [47].
6. Decision making: The decision-making enabler is in level four of the TISM hierarchy, in the upper half of the graph. Various parameters must be considered for making decisions related to the PFSC. For example, the temperature of the trucks is significantly dependent on the route length and the number of stops. Hence, the arrival and waiting time of the vehicle need to be considered to decide the route [33].
7. Third-party logistics: Third-party logistics are seen in level three of the TISM hierarchy; this enabler falls under the second quadrant because of its high driving value and low dependency value in MICMAC analysis. Third-party distribution firms deliver temperature-sensitive food products to different retailers within time-window constraints without affecting food quality. Thus, this problem was modeled with node and arc time window as a VRP and was solved using GA [1].
8. Vehicle routing: In the TISM hierarchy, vehicle routing belongs to level V and is considered one of the most driving enablers, falling under the second quadrant. An artificial fish swarm algorithm was proposed to solve the VRP by considering constraints such as dispatching time, type of vehicle, energy consumption, and vehicle capacity [37]. Effective vehicle routing results in the minimization of cost and emissions.
9. Unit capacity: Unit capacity falls in level I of the TISM hierarchy, and according to MICMAC analysis, it is in the first quadrant and is considered an autonomous type. Transportation and inventory holding unit capacities must be considered during PFSC modeling [34,47].
10. Fuel consumption: TISM hierarchy level II accommodates this enabler. According to MICMAC analysis, it is an autonomous type because it is in Quadrant I. The main objective of vehicle routing is to optimize the total logistic cost, which includes the fuel consumption cost. This objective can be achieved using a multi-objective evolutionary algorithm [28]. Being temperature-dependent, perishable products require extra fuel to maintain their quality. Hence, identifying the path that uses less fuel for refrigeration and traction should also be considered an objective [23,35].
11. Cost–benefit analysis: This is classified as a linkage enabler because if its high dependency and driving value, and it lies in quadrant III of the MICMAC analysis and the second level of TISM hierarchy. During the inbound and outbound logistics of cross-docking, it is needed to minimize the operational and transportation cost for cost–benefit analysis [48]. All the enablers affect cost directly or indirectly.
12. Freshness-keeping: Freshness-keeping lies in level four of the TISM hierarchy, which falls under quadrant I and is considered an autonomous type. Its significance in perishable products is due to shelf life deterioration during transportation. The freshness of the product must be maintained throughout the SC, which directly relates to the selling price of the product and the related wastage. [24,27].
13. Global warming: Global warming is seen in level I of the TISM hierarchy. This enabler is one of the most dependent enablers and falls under the fourth quadrant due to its high dependency and low driving values. Perishable products require refrigeration in SC during transportation to reduce product waste. Greenhouse gas emissions occur throughout, due to refrigeration gas leakage and high energy consumption. Thus, a mixed-integer problem has been developed to reduce global warming and total costs [38].
14. Carbon emission: Lying in level III of the TISM hierarchy, carbon emissions are one of the most dependent enablers, falling in the fourth quadrant. Apart from the total cost,

optimizing the carbon emissions in SC is challenging. Such a problem was solved using a multi-objective evolutionary algorithm [28].

15. Energy utilization: Energy utilization is in level I of the TISM hierarchy and falls under quadrant III. The enabler is considered a linkage enabler according to MICMAC analysis. Refrigeration in transportation causes high energy utilization in PFSC, resulting in high carbon emissions [33].

6. Implications

This paper has identified the enablers of the perishable supply chain. Even though there are multiple studies on PFSC in the literature, a systematic method for identifying and classifying enablers is not present. Moreover, TISM is an established approach for identifying the interrelationships among the enablers and classifying them based on the hierarchy; however, to the best of the researchers' knowledge, no published studies exist that apply TISM for PFSC management. As a result, the current study employs the deterministic (TISM–MICMAC) methodological approach, which has been shown to be effective in identifying the important driving elements by listing complicated, interrelated components on a hierarchical level. Furthermore, the interrelationships among the enablers have been measured with the help of an expert's rating. The levels of each enabler have been identified based on the experience and knowledge of the experts from various areas through an online survey. Finally, due to demand uncertainties of perishable products, the importance or level of each enabler may be altered during disruptions [49].

7. Conclusions

This study identifies fifteen significant enablers that influence PFSC during CC. Vosviewer network visualization software identified fifteen significant enablers with bibliometric data from the SCOPUS database. Later, using the TISM and MICMAC approaches, we analyzed the effect of enablers, mutual relationships, relative importance, and driving and dependency values of the enablers. These results provided the hierarchy levels of each enabler that influences the PFSC. According to this deterministic assessment model, most of the enablers fall in the upper half of the MICMAC graph due to their high driving values. From the above findings, we conclude that 1, 3, 5, and 8 enablers are in level V; 6, 11, and 12 enablers are in level IV; 7 and 14 enablers are in level III; 2, 4, and 10 enablers are in level II; and 9,13 and 15 enablers are in level I. According to TISM-MICMAC analyses, RFID, shelf life, vehicle routing, and inventory control are critical enablers that must have high priority. The driving values of RFID, shelf life, vehicle routing and inventory control are 11, 13, 12 and 14, respectively. The obtained critical enablers and their hierarchies provide valuable insights for researchers in the context of PFSC for further study.

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