Interval Valued Intuitionistic Fuzzy Digraph Matrix Approach with PERMAN Algorithm for measuring COVID-19 Impact on Perishable Food Supply Chains

Abstract

The outbreak of COVID-19 has prompted a substantial shrinkage in various businesses worldwide, the perishable food sector being one of the worst hits. Henceforth, this manuscript intends to analyse the impact of COVID-19 on perishable food supply chains (PFSC) of developed and developing countries. For this, the study presents the analysis in two steps. In the first step, the study illuminates the particular factors that frame unique sorts of supply chain (SC) disturbances in PFSC. Secondly, the study proposes a unique interval-valued intuitionistic fuzzy set (IVIFS) based graph theory and matrix approach (GTMA) to analyse the COVID-19 impact index value. In addition to this, the PERMAN algorithm is used to calculate the permanent function. The study has revealed that developing nations should focus more on their technological and infrastructural factors to improve the condition of PFSC during the pandemic. This study's results can be deployed by decision-makers to forestall the operative and long-haul consequences of COVID-19, or any other disruptions to the PFSC, and make plans to overcome the impact. The significance of this manuscript is that the prominent factors degrading the performance of PFSC amidst the pandemic have been highlighted, with their respective impact on developed and developing nations compared. Moreover, a neoteric comprehensive integration of IVIFS-GTMA technique along with the PERMAN algorithm has been utilised in this manuscript. This particular study is inimitable as it supplements existing literature by providing analytical support to the relationship among various factors impacting the PFSC amidst the pandemic.

Keywords: Perishable Food Supply Chain (PFSC); Food Supply Chain (FSC); Multi-Criteria Decision Making (MCDM); Interval-valued intuitionistic fuzzy set (IVIFS); Graph Theory and Matrix Approach (GTMA); PERMAN algorithm

1. Introduction

The Coronavirus Disease 2019 (COVID-19) has cast an evil spell on the flourishing food industry. The pandemic not only spoiled conventional food practices but also disrupted the fundamental operations that provide us with food, that is, the food supply chain (FSC) (Ivanov, 2020; Xu et al., 2020). FSC circumscribe different supply chains functioning for different types of food items, and this manuscript specifically focuses on perishable food supply chains (PFSC). PFSC incorporate the supply chains for all perishable food items, that is, they lose their value over a particular period. The principal reason for considering PFSC was it being the worst hit sector amidst COVID-19. Unlike other food items, perishable food, such as vegetables and meat, needs preferential treatment in managing its supply chain. Drastically lower shelf life, optimised transportation route, refrigerated storage containers, temperature-sensitive warehouses and high demand uncertainty for seasonal items are some of the prime causes which differentiate a PFSC from a traditional food supply chain. COVID-19, the most neoteric pandemic the world has seen, has just added to these vulnerabilities of PFSC degradation. The coronavirus pandemic is classified under specific disruption; it is extremely solid, quick to impact and disturbs the entire supply chain's functioning (Ivanov et al., 2017; Xu et al., 2020; Sahoo et al., 2021). This disruption caused a lack of adequate feedstock, transport delays, income cut-offs and decreased efficiency emanating from the unavailability of manufacturing amenities, distribution outlets and shipping utilities (Dolgui et al., 2020). Also, it is a little different from other specific disruptions as it commenced gradually from a particular region but spread rapidly, encompassing a vast area (Nikolopoulos et al., 2020). Governments worldwide announced a nationwide lockdown to tackle coronavirus contagion (Verma et al., 2020). The lockdown and border restrictions heavily impacted the perishable food sector, causing product prices to fluctuate (Aday & Aday, 2020; Dash et al., 2021). Also, there have been significant changes in product-specific data and customer behaviour that have worsened the effect of SARS-Cov-2 on the perishable food supply chain (Singh et al., 2020). PFSCs throughout the globe, being exposed to this pandemic, struggled hard to survive during these challenging times. Also, the necessity for indispensable food items rose during this period, with perishable food items being crucial elements of the demand. On the contrary, the increase in need does not increase sales due to the various disruptions in PFSC. These disruptions are caused by supply failures amidst unprecedented lockdowns, closure of numerous PFSC outlets due to the pandemic and rumours of PFSC items being unsafe for consumption. Considering the demand and its fulfilment, PFSC needs to be adequately analysed to search for possible mitigation to arising problems. Although there is sufficient literature on the influence of COVID-19 on the FSC (Aday & Aday, 2020; Mahajan & Tomar, 2020; Singh et al., 2020), there are no satisfactory studies accessible in terms of the perishable food supply chain. Additionally, there has been no research that specifically compares developed and developing countries based on the impact of the global pandemic on their PFSCs. Considering this scenario, this manuscript is dedicated to filling the gap in disruptions caused due to the pandemic on PFSC in the context of both developed and developing countries. The United Nations divides countries into two primary categories: industrialised countries and developing countries. Countries are classified depending on their economic position, such as GDP, GNP, per capita income, industrialization, the standard of living and so on. In comparison to other nations, a developed country is a national entity whose economy has advanced significantly and which has a strong technical infrastructure. Developing nations are those with low levels of industrialisation and a low human development index. Henceforth, it becomes significant to compare how the respective PFSCs of these nations are managing to cope with COVID-19 and how mitigation can be made in specific sectors. The importance of this manuscript is the usage of a neoteric integrated methodology, interval-valued intuitionistic fuzzy set (IVIFS) and graph theory and matrix approach (GTMA) with the PERMAN algorithm, to deal with the identified issues. Moreover, the study has recognised the potential factors challenging the PFSC amidst the COVID-19 pandemic, analysing the impact of recognised factors on developed and developing nations. This study sets out to answer the following research questions:

i. What are the various factors impacting the PFSCs of developed and developing countries during the pandemic?
ii. What is the importance of individual factors on each other in the integrated framework?
iii. How have the factors affected the PFSCs of developed and developing nations during the COVID-19 pandemic?
iv. What are the practical and research implications of the proposed study?

The manuscript tries to answer the above questions via the following research aims:

- To recognize various factors impacting PFSC during COVID-19 and build a relationship among them
- To compute the COVID-19 impact index value of the identified factors concerning developed and developing economies
- To formulate comparison coefficients of the main dimensions and propose managerial implications from this research

This manuscript's principal contribution is to utilise an interval-valued intuitionistic fuzzy-based graph theory and matrix approach (IVIFS-GTMA) using the PERMAN algorithm to compare the overall impact of identified factors on developed and developing countries' PFSCs during the pandemic. Existing literature manifests that many studies have applied graph theory and matrix approach to assessing different real-life problems (Agrawal et al., 2016; Faisal et al., 2007; Rao & Padmanabhan, 2007). However, no investigations have integrated the IVIFS and GTMA technique using the PERMAN algorithm to assess the COVID-19 impact index value. The integration of IVIFS with GTMA (IVIFS-GTMA) is because of its forte in obtaining high accuracy in dealing with vague data (Abdullah & Najib, 2016). This study seeks to make a significant contribution to decision-makers and managers by providing a transparent scenario of PFSC from various developed and developing areas through the pandemic.

The remaining manuscript is arranged as follows. In section 2, the literature associated with PFSC has been reviewed. Section 3 describes the various factors influencing the PFSC of developed and developing countries throughout the pandemic. This can facilitate decision-makers in devising proper strategies to tackle their specific issues. Section 4 explains the solution methodology. Section 5 presents the discussion comprising of implementation of the proposed framework in the case illustration. Section 6 corresponds to the conclusion, illustrating the results takeaways, implications for practice and future research, and sensitivity analysis, and delivers the concluding notes.

2. Literature Review

Perishable food supply chains are comprised of different parties involved in fulfilling the perishable food needs of the end consumers (Kumar et al., 2021; Rossi et al., 2021) . Perishable food encompasses the food items which have comparatively lower shelf lives, and thus, need to be stored in refrigerated containers (Orjuela-Castro et al., 2021; Shanker, et al., 2021) . The various stages of PFSC, involving suppliers, processors, distributors, retailers and customers, have all been prime casualties of the global pandemic (Kumar et al., 2022; Sharma et al., 2022). The unpredicted fluctuation in demand, time and temperature-sensitive logistics handling coupled with low sustainability power are some of the key factors to be addressed during the pandemic (Liu et al., 2022; Mirabelli & Solina, 2022). Henceforth, a study dedicated to recognising the potential challenging factors to PFSC, and their proper analysis, becomes significant at this stage.

A review of relevant research has encountered numerous studies, specifically on the PFSC. In 2015, Siddh et al. (2015) examined PFSC quality and addressed various critical issues. The scrutinized issues were information exchange, logistics handling, strategy devising, demand planning and alignment among the multiple stages of PFSC. Subsequently, Balaji & Arshinder (2016) recognised 16 causes of perishable food wastage in Indian fruit and vegetable FSC and modelled the interactions among the causes by utilizing total interpretive structural modelling and a fuzzy MICMAC approach. Their results indicated that food waste is caused by a huge number of intermediaries and a lack of scientific harvesting methods. Analogously, Prakash et al. (2017) analysed the risks associated with the perishable food supply chain and presented a methodology to deal effectively with all the risks present in PFSC. The authors considered a case in the Indian dairy industry and found that supplier side risks are more influential followed by market risks and process risks.

Recent years have produced various studies specifically based on analysing the influence of COVID-19 on the food sector. Mahajan & Tomar (2020) assessed the numerous disruptions caused in the PFSC due to the advent of COVID-19. Their findings reveal that throughout the ongoing outbreak, long-distance food supply networks have been struck hardest, with ensuing negative effects for urban consumers and farmers. Subsequently, Aday & Aday (2020) reviewed the influence of COVID-19 on the agriculture and food sectors. They concluded that supply chains must be flexible to accommodate the fluctuations of a pandemic. In the same manner, Sharma et al. (2020) analysed the risks in the agricultural supply chain (ASC) due to COVID-19 by utilising Fuzzy Linguistic Quantifier Order Weighted Aggregation (FLQ-OWA). The authors deduced that supply risks, financial risks, demand risks, management and operational factors, logistics and infrastructure risks, biological and environmental risks as well as policy and regulation, all have a crucial influence on ASC; enterprises must show flexibility in scope and scale. Kumar et al. (2020) studied challenges to the application of sustainable practices in PFSC from the perspective of developing economies. The outcomes of their holistic approach suggest that the most crucial challenges to PFSC sustainability are "lack of horizontal integration of farmers," "poor pre-harvest management" and "lack of government regulation and support." Moreover, Clapp & Moseley (2020) concluded that COVID-19 marks an inflexion point, and henceforth a demand for a different set of policy responses that emphasize transforming food supply chains primarily. Consequently, Zanjani et al. (2021) assessed a resilient food supply chain by designing an effective model where pandemic disruptions are modelled as a compound stochastic process; a Monte Carlo procedure is designed to produce probable circumstances. Kumar et al. (2021) evaluated possible mitigation strategies to cope with the disturbances triggered by the pandemic in the PFSC. Their results claimed that “collaborative management” and “proactive business continuity planning” are the prime risk mitigating strategies. Shanker et al. (2021) focused on the possible measures to be taken to enhance the resiliency in the PFSC sector. Their study found that the key ‘cause’ group variables are restrictions on import-export and fear of violating social distancing rules; price volatility of perishable items, panic purchasing and hoarding is the critical 'effect' group factors impacting PFSCs.

It can be deduced from the available literature that much research has been conducted in the food sector with a focus on the pandemic. However, less attention has been given to the field of perishable food supply chains, which form a crucial part of the food industry. Furthermore, none of the research works has explored assessing the PFSCs of developed and developing nations amidst the pandemic. This study, therefore, focuses on bridging the present literature gap by analysing the effect of COVID-19 on the PFSCs functioning in various developed and developing economies.

3. Factors Influencing PFSC During the Pandemic

In literature, a crucial area is to assess the comparison between multiple criteria and develop an appropriate model to uplift them (Tran et al., 2020). The model development process starts with the literature survey and selects the most affecting factor. To accomplish this, raw data associated with the topic has been collected from available literature and reports. After developing a preliminary list of 37 identified factors, specialist views were taken into account for the final screening. A total of 25 specialists were considered, 8 from an academic background and 17 industrial experts. During the final screening process, 15 factors were eliminated, because either they merged with another existing factor or they were not considered to be sufficiently relevant. Thus, a final list of 22 factors was prepared and possible relationships among them were investigated with the advice of the specialists. Finally, the factors' dimensions were categorized based on the existing relationships identified with the help of both relevant literature and chosen specialists. The categorization revealed four principal headings: operational, technological and infrastructural, government policy and regulations plus behavioural. A detailed discussion on these factors is now presented.

3.1 Operational Factors

This section concerns the recognised factors which specifically disrupt the operational segment of PFSC (Lima-Junior & Carpinetti, 2020). Operations refer to the activities involved in transforming a particular product from its raw form to a refined, finished product. Prime activities in operations involve sufficient feedstock, proper production, appropriate transportation, felicitous warehousing along with suitable inventory regulation (Chelbi & Ait-Kadi, 2004). Operational factors have been affected adversely during the pandemic outbreak. This section elaborates on the factors detrimental to the operational activities of PFSC in developed and developing nations.

Table 1(a): Operational Factors

S. No.	Factor	Definition	Influence on PFSC of Developed Countries	Influence on PFSC of Developing Countries	Reference
O1	Restaurant Outlets Closedown	Restaurant outlets are major consumers of perishable products. The complete closedown of these restaurant outlets due to the pandemic depleted the demand for perishable products drastically; the entire PFSC was adversely disrupted.	The figures for restaurant closures in developed economies such as the United States rose to 32,109 by August, with 61% permanent and 39% temporary closures indicating the worsening situation of the restaurant sector; this simultaneously affected the PFSC.	According to the data collected from developing economies such as India, out of 83% of restaurants, 10% had already shut down permanently by July; it is expected that an additional 30% of restaurants will not reopen at all, adversely affecting the PFSC.	(Bialik & Gole, 2020; Zomato, 2020)
O2	Decrement in Price of Perishable Feedstock	The unanticipated lockdown resulted in the closure of various organized and unorganized sectors, leading to a decrease in demand for perishable feedstock. This unforeseen decrease in demand causes a decrement in the price of perishable goods such as meat, fish and milk.	The farmers of Belgium, a renowned developed country, were faced with lower milk exports and decreased prices due to the closure of cafes and restaurants. The decrement in price observed was still less when compared to developing nations.	Pakistan, a developing nation, recorded a decrease in the price of milk of 0.5%-1% from February to April. This fall in the price of perishable goods leads to further degradation of PFSC in developing economies.	(Nordhagen, 2020; Staff, 2020)
O3	Disruption in Cash Liquidity	Cash liquidity is defined as the synchronization between the capital ingoing and outgoing in a supply	Farmers from European developed countries suffered financial hardship as outgoing	Asian farmers from developing countries found it hard to survive and even	(Foote, 2020;

		chain. In the Covid-19 scenario, the amount of cash outgoing is greater compared to the cash incoming to the PFSC; this disrupts the cash flow in the entire supply chain.	cash levels were higher than the cash incoming/held by them; this caused further disruption to the cash flow in European developed countries' PFSCs. However, they managed to survive due to previous cash held them.	meet their basic amenities; they needed immediate support to maintain PFSCs.	Parsai, 2020)
O4	Incompetence in Satisfying Customers	The guidelines issued due to the pandemic restricted proper working of transportation services, wholesalers and retail outlets; PFSC stakeholders were thus unable to cater to the demands of customers on a timely basis, in turn decreasing the agility of PFSC.	Developed countries, mostly in Europe, were locked down since March and had strict restrictions to avoid the spread of the virus. Amidst this scenario, PFSC stakeholders used technologies such as drones to satisfy the needs of customers.	Most developing economies based in Asia had issued certain guidelines for lockdown, interrupting the proper working of PFSC. Developing nations, could not afford the requisite expensive technologies, leading to customer dissatisfaction.	(Anand, 2020; Sandford, 2020)
O5	Degraded Delivery Potential	Timely deliveries during the pandemic have become a major challenge for enterprises as they receive double the number of orders than usual while simultaneously working with only 50-60% of their total workforce, owing to the cancellation of orders.	The advent of coronavirus has caused European start-ups to work with 40-50% of their workforce. A reduced workforce tends to increase the number of cancelled orders, decreasing perishable supply chain responsiveness.	Renowned start-ups of South Asian countries have laid off half their working force, leading to degraded delivery potential. The delivery capability has been depleted more in developing countries due to strict guidelines.	(Lomas, 2020; Marston, 2020)
O6	Escalated Transporting Prices	The transportation sector plays a prominent part in the PFSC, as it ensures proper delivery of inventory to different stakeholders at the right time. Amidst the coronavirus pandemic, truckers have increased their costs by 80%, creating problems in perishable food transportation.	Transportation-associated costs have escalated to such an extent in developed countries that it has become difficult to manage capital flow in their PFSCs.	Local PFSCs of developing countries are the worst hit due to pandemics. These local enterprises are incapable of bearing such high costs, in turn leading to the decline of their businesses.	(Chowdhury, 2020; Lomas, 2020)

3.2 Behavioural Factors

This section explores the factors originating from human behaviour which are disrupting the PFSC amidst COVID-19. Behavioural factors are due to personality, circumstance or response to the surroundings (Salmons & Wilson, 2009). During the pandemic outbreak, these factors magnified to a greater extent and adversely affected the performance of PFSC. This section presents a detailed description of behavioural factors influencing PFSC during the pandemic outbreak.

Table 1(b): Behavioural Factors

S. No.	Factor	Definition	Influence on PFSC of Developed countries	Influence on PFSC of Developing countries	Reference
B1	Panic Purchasing due to Mass Consternation	The coronavirus pandemic has caused a sense of fear among the populations of the entire world. People are moving towards stockpiling, which in turn is creating a shortage of essential perishable food items, adversely affecting the entire PFSC.	Stockpiling became a major concern among Americans when people started panic buying foodstuffs; inventories started reducing at an alarming rate, disrupting the inventory flow in PFSC.	In Asian developing countries like India, people have been stockpiling to such an extent that reports from retailers about food and vegetable items being out of stock increased by 15.8%.	(Bekiempis, 2020; Buchholz, 2020)
B2	Prevalent Misleading Rumours	Fake rumours spread through social media that birds might be possible carriers of the virus, causing the poultry trade to decline significantly worldwide, worsening the situation of PFSC.	Developed countries were mainly non-vegetarians; thus, fake rumours were not comparatively so influential on them.	Most major developing economies with links to South Asia were badly hit by fake rumours; chicken sales were slashed by almost 50% in these nations.	(Sandford, 2020; The Times of India, 2020)
B3	Psychological Effects of Safety Precautions	Social distancing has emerged as a significant precaution during the coronavirus outbreak. Given these circumstances, people prefer not to visit crowded places such as local markets, leading to a slump in trade for wholesalers, retailers and vendors.	European developed countries are the worst hit by this pandemic as reports of positive cases of coronavirus are escalating. People are avoiding purchasing from local vendors, but the situation is manageable as a large section of the	Asian developing economies are densely populated, making it difficult for them to adjust to the current scenario of Covid-19. Due to social distancing, the operation of PFSC local vendors has come to a halt.	(Nordhagen, 2020; World Health Organisation, 2020)

			population does not depend on local PFSCs.		
B4	Heuristic Approach to Purchasing	Amidst the coronavirus pandemic, people are following the heuristic approach of buying; they purchase food items by recognizing their brand name, value and product image, ending up buying branded products. Thus, local PFSC is suffering due to a lack of demand.	European local food markets have collapsed due to the coronavirus pandemic. The heuristic approach of buying is worsening the situation for local PFSCs as their demand is declining.	Local PFSCs contribute to a large sector of food supply chains in Asian countries. Purchasing by keeping in mind the brand name and popularity has led to the demise of local products, in turn affecting the local PFSC adversely.	(Bialik & Gole, 2020; Staff, 2020)
B5	Less Physical Buying	The ease of online purchasing has resulted in a significant reduction in the demand for local goods. These factors collectively deteriorate the condition of markets and PFSCs operating at a local level.	Developed economies were already sufficiently advanced in online purchasing, meaning they already possessed a well-defined framework integrating local PFSCs with the internet. Thus, they remain majorly unaffected.	Online buying culture is still inculcating among citizens of developing countries; this has escalated due to Covid-19. With less preference given to local markets and products, the result is a decline in local PFSCs.	(Foote, 2020; Redman, 2020)

3.3 Government Rules and Regulations

This section incorporates the factors emerging due to government rules and regulations worldwide, and which have adversely affected PFSC functioning (Ivanov, 2020). Factors such as nationwide lockdown and social distancing affected the working of PFSC to a large extent (Lomas, 2020). This section discusses various government rules and regulatory factors which influenced PFSC during the pandemic.

Table 1(c): Government Rules and Regulations

S. No.	Factor	Definition	Influence on PFSC of developed countries	Influence on PFSC of developing countries	Reference

G1	Restrictions on Local Markets	Economies around the world had implemented nationwide lockdowns under which local markets suffered greatly due to the imposed restrictions. As a result, wholesale rates decreased due to less demand whereas retail rates increased, affecting both the farmers and customers adversely.	Developed economies like the United States started their first lockdown in March, continuing for about 8 months. Throughout this period, local markets were worst hit due to the restrictions imposed on them.	India, one of the major developing nations, announced a nationwide lockdown starting in March; this lasted for about 2 months. Local markets *(Mandis)*, a major part of perishable local markets, were not able to function adequately due to the lockdown rules.	(Anand, 2020; Sandford, 2020)
G2	Restraints on International Trade	The condition of global perishable food supply chains continued to degrade due to the absence of international trade. Countries closed their borders to cope with the pandemic, eventually stopping the import and export of perishable fruits and vegetables; this created a major problem for PFSC stakeholders.	With the commencement of the nationwide lockdown, most European countries shut down their international borders to avoid any further spread of the contagion; thus, international trade suffered.	After a time, the restrictions on domestic movement were laid off in developing Asian countries, yet international movement was still restricted.	(Buckley & Spurrell, 2020; Guest, 2020)
G3	Unanticipated Nation-wide Halt	Nations around the world implemented lockdown amidst the coronavirus pandemic. This unexpected halt not only affected internal and external trades but also the perishable food feedstock since the disruption took place around harvest time – a very significant time for farming.	Developed European economies closed in March for their first lockdown. To counter the second wave of the pandemic, nations like the United Kingdom announced a second lockdown in November. Throughout this period, both internal and external trades associated with PFSC have significantly been affected.	Asian developing countries have just ended the first lockdown and are still battling with the second wave of contagion. The fluctuations in infection rates mean that restrictions have not been lifted completely, adversely affecting the functioning of PFSCs.	(BBC, 2020; Diplomat Risk Intelligence, 2020)

G4	Dearth of Proper Rules in Dairy, Poultry and Marine Sectors	The coronavirus outbreak adversely affected the perishable food trade both at national and international levels of different nations throughout the world. In these uncertain circumstances, rumours circulate related to dairy, poultry and marine products being risky. To tackle these issues, proper rules are needed.	The coronavirus pandemic has been a hard time for developed countries, but the worst hit was the poultry and marine sector. Demand for these products decreased drastically. The poultry and marine sectors need a new set of guidelines to support livelihoods.	The poultry and marine sectors of developing countries have suffered hardest throughout the pandemic because of the collapse in their sales. The absence of proper guidelines has led to further decline in these sectors.	(European Union, 2020; The Times of India, 2020)
G5	Fastening of State Borders	To handle the coronavirus pandemic, states of different countries around the world sealed their borders to avoid the further spread of the disease. The flow of perishable goods was hindered to a large extent.	In time, developed countries also started sealing their states and cities. Incoming and outgoing perishable food logistics were affected, disrupting the PFSC.	Developing countries like India fastened their state borders to avoid further infection, disrupting the flow of perishable stock.	(Diplomat Risk Intelligence, 2020; Tiwary & Ghosh, 2020)
G6	Shortage of Employees	Governments of nations around the world cut workforces to only 50-60% capacity to avoid the infection from spreading. A reduced workforce led to factors such as delays and cancellations in orders, paving the way to poor performance of PFSCs.	After the complete lockdown was eased, enterprises of developed countries were forced to work with a reduced workforce, leading to poor responsiveness.	PFSCs of developing countries suffered due to the guidelines of governments of operating with a reduced number of workers, depleting the agility of their PFSCs.	(Lomas, 2020; Marston, 2020)

3.4 Technological and Infrastructural Factors

This section presents the factors associated with technology and infrastructure that influenced PFSC during the pandemic in developed and developing economies. Technology is an essential component that plays a significant part in the management of PFSC (Research and Markets, 2020). The pandemic led to various technological disturbances. These combined with previously-existing discrepancies make significant disruptions for the PFSC. This section describes the technological and infrastructural factors responsible for degrading PFSC amidst the pandemic.

Table 1(d): Technological and Infrastructural Factors

S. No.	Factor	Definition	Influence on PFSC of Developed countries	Influence on PFSC of Developing countries	Reference
T1	Impoverished Transportation System	Factors like untrained labour and a lack of refrigerated vehicles during the crisis combined to form a poor transportation network, creating a hurdle for the proper functioning of PFSC.	Developed economies already had resources such as refrigerated vehicles and trained workers to a satisfactory level. However, the Covid-19 pandemic produced a demand for more refrigerated vehicles, and thus its market is expected to rise in upcoming years.	Developing countries were lacking in adequate refrigerated vehicles for transporting perishable food products from the pre-COVID-19 era. The pandemic led to escalating problems associated with perishable product transportation.	(Marston, 2020; Research and Markets, 2020)
T2	No-contact Delivery Issues and Improper Staff Screening	Contactless delivery remains a significant challenge during the pandemic. Proper screening of staff members and delivery persons is an essential part of managing PFSC; this is proving to be difficult for economies around the world.	Drone technology is being used by some of the major developed countries such as Australia and Canada to tackle the contactless delivery issue. Though installation costs are high, they have been proven as a successful technique to cope with the current scenario.	Developing countries lack sufficient funds and resources to increase the scope of implementation of technologies like drones; thus, they remain limited to some cities only. Furthermore, economies like India have reported several cases of delivery boys being infected, a worrying issue for PFSC management.	(India Today, 2020; We Robotics, 2020)
T3	Limited Scope of E-commerce platforms related to Perishable Products	The pandemic demanded the need for social distancing meaning that many people shifted towards e-commerce platforms to purchase perishable products. The limited scope and availability of online platforms created a hurdle for PFSC management.	Most of the population of developed nations are in well-resourced cities and thus have access to online platforms for perishable food delivery.	A developing nation has under-developed cities to a large extent with the major portion of the country's population belonging to these under-developed areas. People are largely deprived of online resources and are thus unable to fulfil their needs related to perishable food.	(Foote, 2020; Redman, 2020)

T4	Manipulation in Information and Bullwhip Effect	Increased demand for perishable goods in households during the global pandemic is leading to more claims at the local retail store, further resulting in more claims to the wholesaler, creating a bullwhip effect in the PFSC. This bullwhip effect is responsible for excess inventories, distorting the PFSC information flow.	The bullwhip effect can be seen clearly in intensely developed European economies, which consequently leads to the increment of inventory size without any specific use.	Developing countries in South Asia have faced the bullwhip effect of PFSC; the upstream producer, usually the farmer, becomes uncertain regarding the quantity, consequently leading to uncertainties in lower inventory forecasts.	(Parsai, 2020; Perdana et al., 2020)
T5	Conventional Packaging Practices and Improper Packaging	Proper packaging is essential at the time of the coronavirus crisis to ensure full safety and precautions. Conventional packaging practices need to be retransformed to cater to the needs of the current situation; this is a major challenge for PFSC managers.	Developed countries such as Germany and Taiwan have per capita packaging consumption of 42 kg and 19 kg, respectively, indicating that it is not a major issue for developed countries to cope with more elaborate packaging practices.	The per capita packaging consumption in developing countries like India is quite low at 8.7 kg, due to the conventional culture of buying unpacked items. This creates a major problem for these economies to deal with PFSC management during the pandemic.	(Lomas, 2020; Marston, 2020)

4 Solution Methodology

This research incorporates the utilization of an integrated framework comprising IVIFS and GTMA using the PERMAN algorithm for effectively recognizing and computing various supply chain disruptions in the context of PFSC. For an enhanced understanding of the problem, a typical PFSC structure has been developed in Figure 1 where the action areas of recognised factors have been highlighted. For example, in the first stage of PFSC, for farmers or organisations, the risks B2, O2 and O3 are actionable; these are deteriorating the performance at this stage. Similarly, the other mentioned risks along with their specific areas of impact in the PFSC have been shown in Figure 1. The responsibilities of each stage of PFSC have also been discussed in Figure 1.

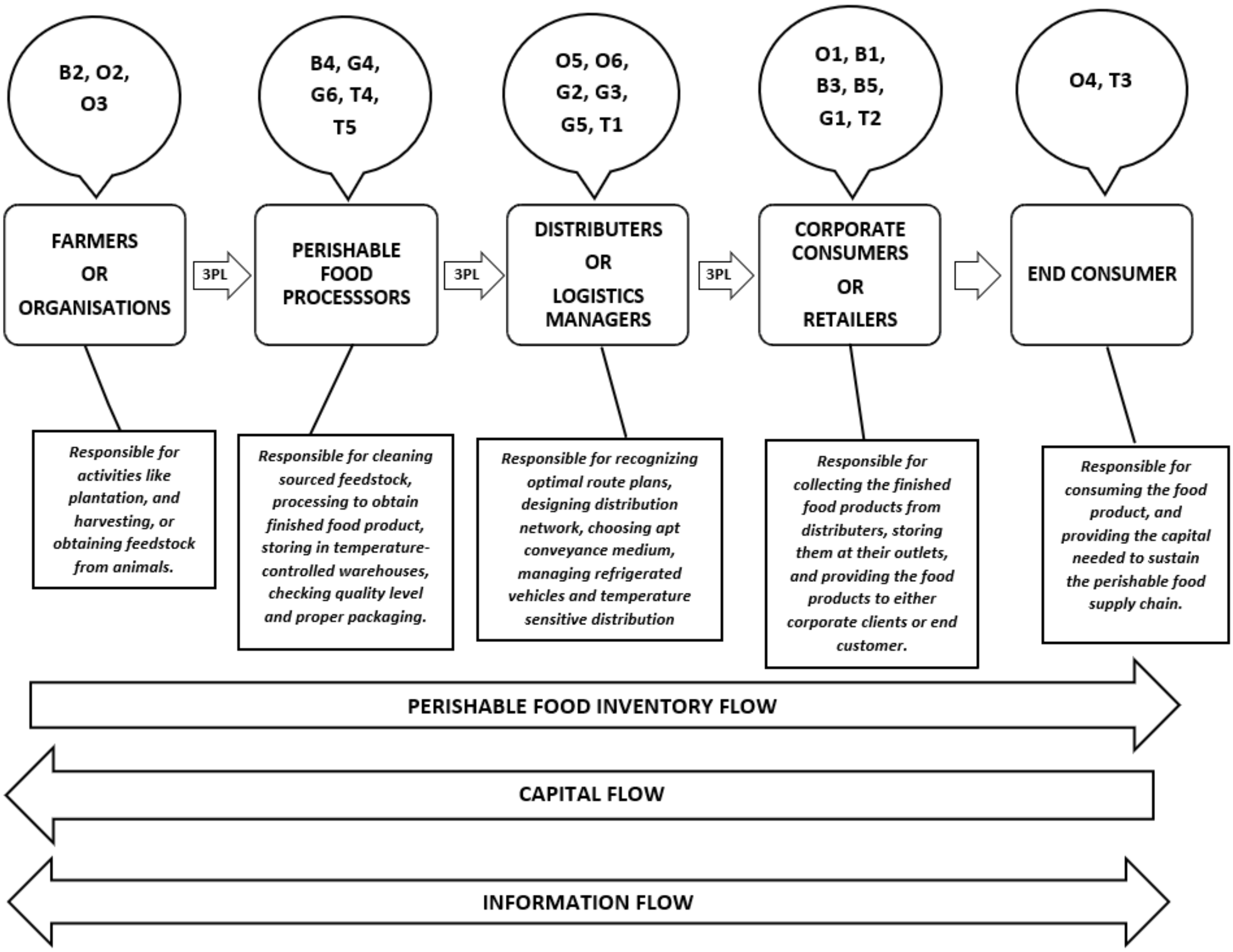


Figure 1: Impact Areas of Recognised Risks in a Typical PFSC, along with Responsibilities of Each Stage

Additionally, to ensure understanding of the proposed framework, a flow of study has been developed, as represented in Figure 2.

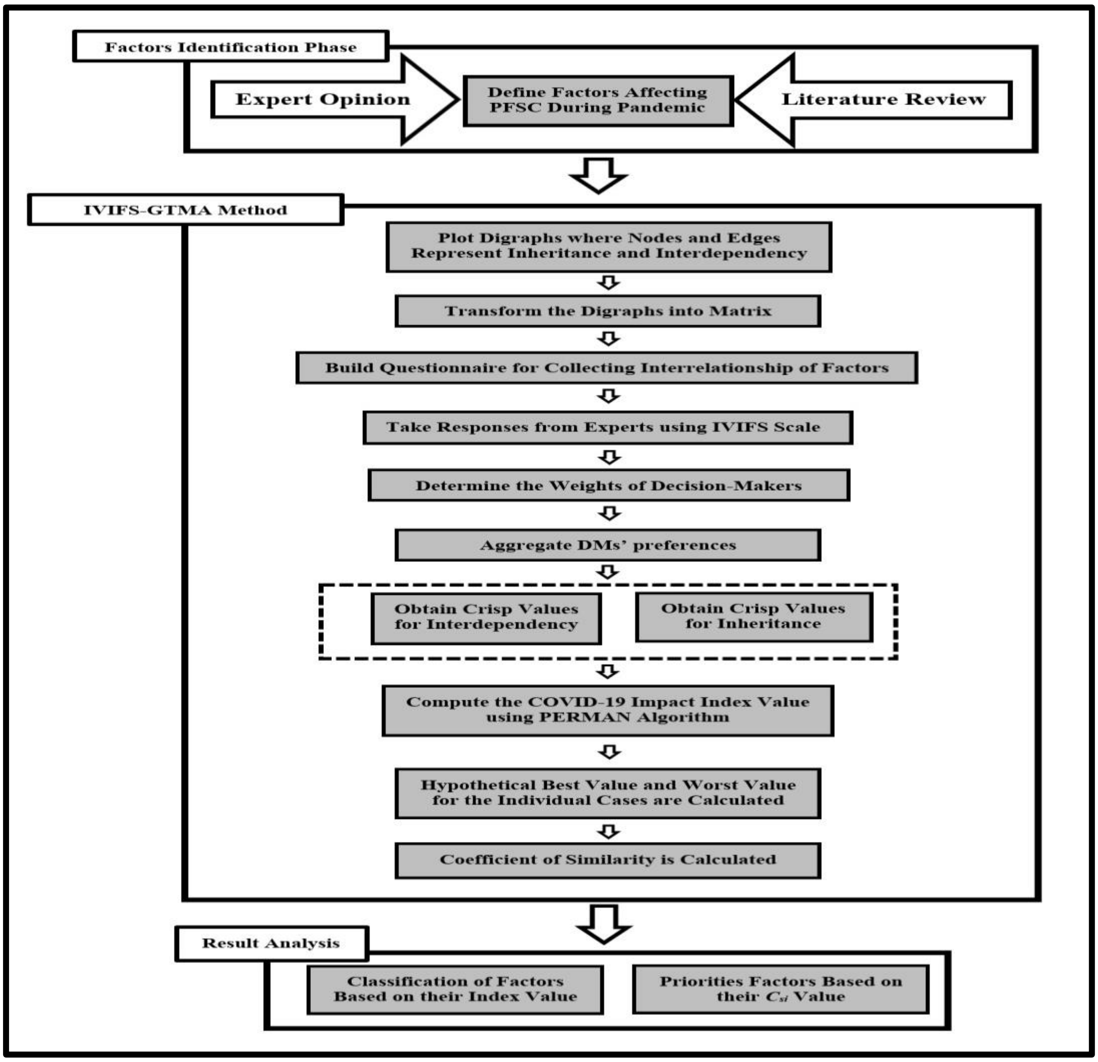


Figure 2: Flow of Study

The IVIFS was proposed by Atanassov and Gargov (1989) as an extended version of IFS. IVIFS characterizes non-membership, membership and hesitancy function as intervals. The objective behind incorporating intervals instead of crisp values lies in the struggle of crisp values in dealing with the human mind. Considering this aspect, fuzzy membership degrees were utilized to compute decision-makers' choices (Zadeh, 1965). Despite the widespread utilization of fuzzy sets, it fails to compute the degree of hesitancy in human judgment. To tackle this issue, IFS was proposed initially which depicted the membership, non-membership and hesitancy degrees, thereby facilitating decision-makers to determine their choices correctly by taking into account the degree of disagreement. Later, IVIFS was proposed as a modified IFS form. IVIFS outshines other fuzzy decision-making techniques, such as fuzzy membership degree and IFS, by computing the membership, non-membership, and hesitancy degrees in an interval form, rather than crisp values. Henceforth, IVIFS substantiates itself as the most suitable decision-making technique to handle the vagueness present in the problem-solving framework. IVIFS has been widely utilized in research since its formation (Zhang & Yu, 2012; Liao et al., 2014). Tiwari et al. (2020) utilised IVIFS integrated with TOPSIS to recognise the best supplier. The results obtained were in concurrence with other well-known Fuzzy TOPSIS methods, demonstrating that IVIFS-TOPSIS can be utilised over other conventional linguistic variable multi-criteria decision making (MCDM) techniques. Perçin (2021) utilised IVIFS integrated with the Analytic hierarchy process (AHP) and Complex proportional assessment (COPRAS) methodology to solve the problem of circular supplier selection (CSS). This study combines IVIFS with graph theory and a matrix approach to assess the adverse impact of factors on PFSC during the pandemic. GTMA helps in better understanding the problem through visual analysis of the system elements and their interdependencies. It also offers the benefit of the matrix representation of the problem which could be processed through computers. These benefits have attracted researchers to analyse their problems from several domains including manufacturing (Goyal & Grover, 2013; Kumar R. & Kumar, 2016), logistics (Mangla et al., 2019; Tuljak-Suban & Bajec, 2020), quality (Jain & Raj, 2014, 2016), supply chain risk mitigation (Muduli et al., 2013), outsourcing decisions (Agrawal et al., 2016) and servitisation model quality (Mishra et al., 2020). This motivated us to employ the tool in our research.

GTMA, which draws from the advanced theory of graphs and networks, is a branch of combinatorial mathematics (Mishra et al., 2020) and has been manifested to be a dominant tool for modelling and analysing stochastic processes, transportation networks and several other systems (Muduli et al., 2013). This technique aids visualization of the problem through a digraph that incorporates nodes or vertices and directed arrows; nodes represent the system components while arrows represent the nature of interactions among these components. The three constructs of GTMA are as follows:

i. Illustration of the system and its components with the help of digraphs that facilitate visual analysis
ii. Representation of the factors and their interaction in a matrix format for computer processing
iii. Permanent function calculation, which is suitable for expressing each dimension's effect by a single number or index

GTMA possesses an advantage over typical illustrations which also offer a visual representation of the problem. GTMA can portray the interplay among elements of the problem and represent it in a mathematical model; this is lacking in the case of the other techniques mentioned above (Muduli et al., 2013; Muduli and Barve, 2013). The present case incorporates the quantification of the impact of COVID-19 on PFSC of developed and developing countries; this is not possible by any of the above-discussed methods except GTMA. Since its introduction, the GTMA approach has been utilized in different decision-making environments for the computation of disruption impact (Rao, 2007, 2013). A flow chart illustration of the proposed methodology, that is, an integration of IVIFS and digraph-matrix approach, is shown in Figure 1.

This study uses the PERMAN algorithm developed by Nijenhuis et al. (2015) instead of the Ryser algorithm, to calculate the permanent function. It is more efficient and less susceptible to finite precision errors than the standard Ryser algorithm. Also, the Ryser algorithm's time complexity is O ($N^2 \times 2^{n-1}$), whereas, for the PERMAN algorithm, the time complexity is O ($N \times 2^{n-1}$). This difference makes the PERMAN algorithm faster and more appropriate in cases where N is high (Nijenhuis et al., 2015).

According to the above-mentioned characteristics exhibited by the listed methodologies, the integration of IVIFS and GTMA along with the PERMAN algorithm provides the best decision-making environment for the real-life case study addressed in this paper. The various steps associated with the IVIFS-GTMA technique along with the included formulas are given below.

IVIFS and GTMA using the PERMAN Algorithm

Step I: Identification of the factors affecting the PFSC of developed and developing nations during the pandemic while taking into account their relative interdependencies.

Step II: Digraph development for visualising the PFSC problem given the recognised element and their interdependencies.

Step III: Modification of the digraphs into matrices under Equation (1).

$$G = \begin{pmatrix} E_1 & r_{12} & r_{13} & \cdots & r_{1n} \\ r_{21} & E_2 & r_{23} & \cdots & r_{2n} \\ r_{31} & r_{32} & E_3 & \cdots & r_{3n} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ r_{n1} & r_{n2} & r_{n3} & \dots & E_n \end{pmatrix} \tag{1}$$

where, E_i is the value of the factor demonstrated by node and r_{ij} is the relative importance of i^{th} factor over j^{th} represented by the edge r_{ij}.

Step IV: Taking inputs using IVIFS linguistic terms and conversion into crisp numbers using the steps given below:

- **Description 1** (Atanassov, 1986). Let X be an ordinary finite non-empty set. An IFS A in X is described as

$$A = \{\langle x, \mu_A(x), v_A(x)\rangle | x \in X\}, \tag{2.1}$$

where $\mu_A(x) : X \rightarrow [0,1]$and $v_A(x) : X \rightarrow [0,1]$ are described in a manner that $0 \leq \mu_A(x) + v_A(X) \leq 1, x \in X$. The denotation $\mu_A(x)$ depicts the membership degree while $v_A(x)$ depicts the non-membership degree of the element $x \in X$ to the set A. $\pi_A(x)$ are the hesitance level of $x \in X$ to the set A and $0 \leq \pi_A(x) \leq 1, x \in X$. It is calculated as

$$\pi_A(x) = 1 - \mu_A(x) - v_A(x), x \epsilon X \tag{1.2}$$

- **Description 2** (Atanassov & Gargov, 1989). Let X be an ordinary finite non-empty set. An IVIFS A in X is given by $\tilde{A} = \{\langle x, \tilde{\mu}_{\tilde{A}}(x), \tilde{v}_{\tilde{A}}(x), \tilde{\pi}_{\tilde{A}}(x)\rangle | x \in X\}$, where$\tilde{\mu}_{\tilde{A}}(x) \subset [0,1], \tilde{v}_{\tilde{A}}(x) \subset [0,1], \tilde{\pi}_{\tilde{A}}(x) \subset [0,1]$are intervals, depicting the degree of membership, degree of non-membership and degree of hesitation of the element x in the set A, respectively. $\pi^L_{\tilde{A}}(x) = 1 - \mu^U_{\tilde{A}}(x) - v^U_{\tilde{A}}(x), \pi^U_{\tilde{A}}(x) = 1 - \mu^L_{\tilde{A}}(x) - v^L_{\tilde{A}}(x)$ for all $x \in X$.
- **Description 3** (Abdullah & Najib, 2016). The IVIFN is developed depending upon IFS with the condition $\alpha + \beta \in [0,1]$ where $\alpha x = 0.5$ and $\beta x = 0.5$ are used as the fuzzification. Then, the intervals are written as

$$\left[\mu^L_{(A)}(x), \mu^U_{(A)}(x)\right] = [|\mu_A(x) - \alpha_x \pi_A(x)|, |\mu_A(x) + \alpha_x \pi_A(x)|] \tag{2.3}$$

$$f(S) = \prod_{i=1}^{n} \lambda_i (S) \tag{3.3}$$

$$[v_{(A)}^{L}(x), v_{(A)}^{U}(x)] = [|v_A(x) - \beta_x \pi_A(x)|, |v_A(x) + \beta_x \pi_A(x)|] \tag{2.2}$$

$$[\pi_{(A)}^{L}(x), \pi_{(A)}^{U}(x)] = [1 - \mu_{(A)}^{U}(x) - v_{(A)}^{U}(x), 1 - \mu_{(A)}^{L}(x) - v_{(A)}^{L}(x)] \tag{2.3}$$

- **Description 4** (Xu, 2007). The aggregated value of $\alpha_j = ([\mu_j^L, \mu_j^U], [v_j^L, v_j^U], [\pi_j^L, \pi_j^U])$ utilizing the IVIFWA operator is described as:

$$\begin{gathered} \left(\left[1 - \prod_{j=1}^{n}(1-\mu_j^L)^{\lambda_j}, 1 - \prod_{j=1}^{n}(1-\mu_j^U)^{\lambda_j}\right], \left[\prod_{j=1}^{n}(v_j^L)^{\lambda_j}, \prod_{j=1}^{n}(v_j^U)^{\lambda_j}\right]\right) \\ \left(\prod_{j=1}^{n}(1-\mu_j^U)^{\lambda_j} - \prod_{j=1}^{n}(v_j^U)^{\lambda_j}, \prod_{j=1}^{n}(1-\mu_j^L)^{\lambda_j} - \prod_{j=1}^{n}(v_j^L)^{\lambda_j}\right) \end{gathered} \tag{2.4}$$

where λ_j is the weight of α_j.

Wei et al.(2011) suggested an equation to compute the entropy, particularly for IVIFS.

- **Description 5** (Wei et al., 2011). The fuzzy entropy measure of an IVIFS $([\mu_i^L(x), \mu_i^U(x)], [v_i^L(x), v_i^U(x)], [\pi_i^L(x), \pi_i^U(x)])$ is described as:

$$a_{ij} = E(A) = \frac{1}{n}\sum_{i=1}^{n}\left[\frac{2 - |\mu_i^L(x) - v_i^L(x)| - |\mu_i^U(x) - v_i^U(x)| + \pi_i^L(x) + \pi_i^U(x)}{2 + |\mu_i^L(x) - v_i^L(x)| + |\mu_i^U(x) - v_i^U(x)| + \pi_i^L(x) + \pi_i^U(x)}\right] \tag{2.5}$$

where n is the number of elements in the IVIFS.

Step V: Transformation of these matrices into the permanent function is carried out by utilising the equation given by Nijenhuis et al.(2015), also used in the PERMAN algorithm.

$$x_i = a_{i,n} - \frac{1}{2}\sum_{j=1}^{n} a_{ij} \; (i = 1, \dots, n) \tag{3.1}$$

$$per(G) = (-1)^{n-1} 2 \sum\nolimits_{S}'' (-1)^{|S|} \prod_{i=1}^{n} \left\{ x_i + \sum_{j \in S} a_{ij} \right\} \tag{3.2}$$

where S runs only over subsets of $1, 2, \dots, n-1$. To save the final factor of $n/2$ in the amount of computation needed, for each subset $S \subseteq \{1, 2, \dots, n-1\}$, the following has to be computed.

$$\lambda_i(S) = x_i + \sum_{j \in S} a_{ij} \; (i = 1, \dots, n) \tag{3.4}$$

Suppose the subset S varies from its predecessor S' by a single element, j. Then,

$$\lambda_i(S) = \lambda_i(S') \pm a_{ij}(i = 1, \ldots, n) \tag{3.5}$$

These equations are coded in MATLAB to execute the PERMAN algorithm.

Step VI: Calculation of COVID-19 impact index utilizing PERMAN algorithm.

Step VII: Computation of theoretical best value and theoretical worst value.

Step VIII: Any two situations selected for comparison will be analogous from the perspective of PFSC factors in case their diagraphs are isomorphic or PFSC factors' matrices are indistinguishable (Grover et al., 2004). Usually, two situations are never indistinguishable from the PFSC perspective; a specific factor that influences one specific situation may not affect the PFSC practices of other situations. Thus, an enhanced contrast of two situations can be achieved by assessing the co-efficient of their similarity or dissimilarity (Grover et al., 2004).

$$C_{si} = \frac{\left(C_{ij} - B_{ij}\right)}{W_{ij} - B_{ij}} \tag{4.1}$$

where
C_{si} = Co-efficient of similarity of i^{th} factor with the best value
B_{ij} = Best value of factor i of j^{th}situation
and
$C_{ij=}$Current value of i^{th} factor of j^{th} situation.

The coefficient of similarity of the i^{th} factor with worst value is calculated as

$$C'_{si} = \frac{\left(W_{ij} - C_{ij}\right)}{W_{ij} - B_{ij}} \tag{4.2}$$

where
C'_{si} = Co-efficient of similarity of i^{th} factor with the worst value
W_{ij} = Worst value of factor i of j^{th}situation

C_{si} value indicates more similarity with the best value (or less PFSC influencing intensity). Alternatively, the smaller the value of C_{si}, the lesser is the strength of a factor to influence PFSC. Analogously, the smaller the value of C'_{si} the greater is the intensity of the factor to influence PFSC.

5 Discussion

The case of the disruption caused to PFSCs of developed and developing economies during the COVID-19 pandemic has been selected to apply and validate the proposed framework. As discussed, the detailed process of data assortment and analysis is given in the accompanying subsections.

5.1 Respondent Selection, Questionnaire Development and Data Collection

The factors influencing PFSC during the pandemic are recognised from the literature review and ensure their pertinence in the case study through the specialists' contributions. In this manuscript, specialists correspond to multiple stakeholders; for instance, academicians in the sector of logistics, SC and perishable product companies (8 academicians and 17 industrialists). A total of 53 specialists were approached with questionnaires to contribute to this work with 25 agreeing to respond. The 25 considered specialists all have relevant work experience of over ten years. Details of the specialists along with their qualifications are given in Appendix A.

For interdependence assessment and computation of each factor's impact on PFSC of developed and developing economies, a summed-up poll was circulated to all selected specialists, comprising a scale ranging from "no influence" to "very high influence," as shown in Table 2.

Table 2: The IVIF-GTMA preference scale

Linguistic Preference scale	No influence	Low influence	Medium influence	High influence	Very high influence
IFS	(0.10, 0.80, 0.10)	(0.25, 0.60, 0.15)	(0.50, 0.40, 0.10)	(0.75, 0.20, 0.05)	(0.90, 0.05, 0.05)
IVIFS	([0.050, 0.150], [0.750, 0.850], [0.000, 0.200])	([0.175, 0.325], [0.525, 0.675], [0.000, 0.300])	([0.450, 0.550], [0.350, 0.450], [0.000, 0.200])	([0.725, 0.775], [0.175, 0.225], [0.000, 0.100])	([0.875, 0.925], [0.025, 0.075], [0.000, 0.100])

Sources: Abdullah et al. (2019)

5.2 Computing the COVID-19 Impact Index Value of Factors Affecting PFSC

This section incorporates the computation of the COVID-19 impact index value of PFSCs of developed and developing nations. As mentioned, the steps involved in the IVIFS-GTMA are applied to the above case as follows.

5.2.1 Behavioural digraph

A behavioural digraph is developed to depict the factors influencing the functioning of PFSC in respect of nodes and edges (Fig. 2). Let nodes signify factors and edges embody their interactions. The digraph signifies factors ($E_i's$) by its nodes and the relationship of factors ($r_{ij}'s$) by its edges. r_{ij} indicates the degree of dependence of j_{th} factor on i_{th} factor. In Figure 2, r_{ij} is depicted as a directed edge from node i to node j. Figure 2 embodies the proposed factors and interactions among them. As a result, 22 factors are recognised from the behavioural digraph. Figure 2 displays the behavioural digraph for all factors.

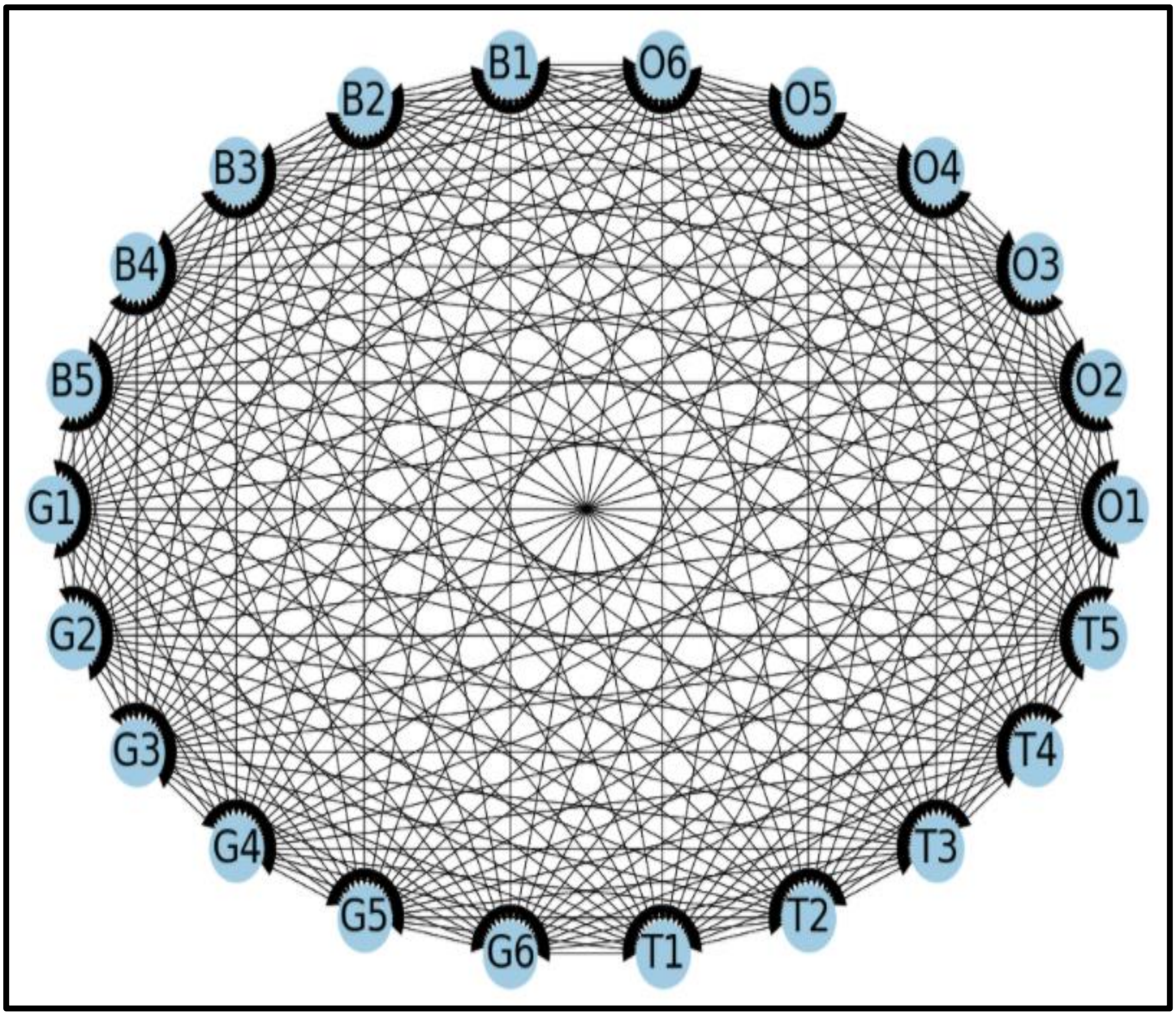


Figure 3: The Behavioural Digraph of the Factors

5.2.2 Matrix Depiction

Matrix depiction of the digraph depicted in Figure 2 provides a one-to-one depiction, as shown in Eq. (1). In our case, the matrix is a 22×22 matrix, as we portray 22 factors influencing PFSC during the pandemic.

5.2.3 Calculation of E_i and r_{ij} values using IVIFS

Step 1: Gather linguistic data utilising IVIFS preference scales developed using Eqs. (2.3) - (2.5), as depicted in Table 2.

Step 2: Find the weights of 25 decision-makers (DMs). The priority order of DMs proposed by Boran et al. (2009) is formulated utilising Eqs. (2.3) - (2.7). Table 2 constitutes the preference scales of DMs depicted in IVIFS rather than IFS.

Step 3: Aggregate DMs' preferences. The IVIFS score provided by the kth DM depicts the impact level that i has on j. DMs' preferences are aggregated and computed utilising Eq. (2.6), which facilitates obtaining the matrix of 22×22. The matrix exhibits all r_{ij} values.

Step 4: Obtain crisp values for r_{ij} using Eq. (2.7). The crisp values are represented in a 22×22, as depicted in Table 3.

Step 5: Repeat steps 3 and 4 to get the crisp values of E_i for developed and developing nations; this is shown in Table 4.

5.2.4 Compute the COVID-19 Impact Index Value from the Crisp Relation Matrices

The COVID-19 impact index value is calculated for developed and developing countries utilising the PERMAN algorithm using Eqs. (3.1) - (3.5). The values of E_i are replaced according to the case and the index value is computed. Also, the index value of each main factor is deduced from the 22×22. The hypothetical best and worst values for individual cases are obtained. The coefficient of similarity for the respective case is calculated for comparison, using Eqs. (4.1) - (4.2) as shown in Table 3.

Table 3: Crisp Values for "r_{ij}"

B1	B2	B3	B4	B5	G1	G2	G3	G4	G5	G6	T1	T2	T3	T4	T5
0.612	0.311	0.070	0.311	0.070	0.311	0.612	0.311	0.163	0.311	0.311	0.311	0.311	0.163	0.163	0.311
0.311	0.311	0.311	0.311	0.311	0.163	0.311	0.163	0.163	0.163	0.163	0.163	0.311	0.311	0.163	0.311
0.311	0.163	0.311	0.311	0.311	0.311	0.163	0.163	0.070	0.311	0.311	0.311	0.311	0.163	0.163	0.163
0.311	0.070	0.070	0.311	0.163	0.311	0.311	0.311	0.311	0.070	0.163	0.311	0.163	0.781	0.070	0.311
0.612	0.311	0.163	0.311	0.311	0.163	0.311	0.311	0.311	0.070	0.311	0.311	0.612	0.612	0.311	0.311
0.311	0.163	0.311	0.311	0.070	0.163	0.311	0.311	0.311	0.070	0.070	0.311	0.163	0.311	0.311	0.311
E7	0.311	0.311	0.163	0.070	0.311	0.311	0.311	0.070	0.070	0.070	0.311	0.311	0.311	0.311	0.163
0.689	**E8**	0.612	0.612	0.163	0.070	0.070	0.311	0.311	0.311	0.311	0.163	0.163	0.612	0.311	0.311
0.689	0.388	**E9**	0.311	0.781	0.612	0.311	0.612	0.311	0.612	0.612	0.781	0.612	0.781	0.781	0.163
0.837	0.388	0.689	**E10**	0.781	0.612	0.311	0.311	0.070	0.311	0.612	0.311	0.163	0.311	0.163	0.163
0.930	0.837	0.219	0.219	**E11**	0.311	0.163	0.163	0.311	0.163	0.163	0.163	0.163	0.311	0.163	0.163
0.689	0.930	0.388	0.388	0.689	**E12**	0.311	0.163	0.311	0.311	0.070	0.070	0.163	0.311	0.163	0.612
0.689	0.930	0.689	0.689	0.837	0.689	**E13**	0.163	0.311	0.311	0.311	0.311	0.163	0.311	0.311	0.163
0.689	0.689	0.388	0.689	0.837	0.837	0.837	**E14**	0.311	0.612	0.781	0.612	0.781	0.612	0.612	0.781
0.930	0.689	0.689	0.930	0.689	0.689	0.689	0.689	**E15**	0.311	0.163	0.612	0.311	0.612	0.781	0.612
0.930	0.689	0.388	0.689	0.837	0.689	0.689	0.388	0.689	**E16**	0.612	0.781	0.612	0.612	0.612	0.612
0.930	0.689	0.388	0.388	0.837	0.930	0.689	0.219	0.837	0.388	**E17**	0.163	0.311	0.781	0.163	0.781
0.689	0.837	0.219	0.689	0.837	0.930	0.689	0.388	0.388	0.219	0.837	**E18**	0.612	0.781	0.311	0.311
0.689	0.837	0.388	0.837	0.837	0.837	0.837	0.219	0.689	0.388	0.689	0.388	**E19**	0.781	0.163	0.612
0.689	0.388	0.219	0.689	0.689	0.689	0.689	0.388	0.388	0.388	0.219	0.219	0.219	**E20**	0.163	0.163
0.689	0.689	0.219	0.837	0.837	0.837	0.689	0.388	0.219	0.388	0.837	0.689	0.837	0.837	**E21**	0.311
0.837	0.689	0.837	0.837	0.837	0.388	0.837	0.219	0.388	0.388	0.219	0.689	0.388	0.837	0.689	**E22**

	O1	O2	O3	O4	O5	O6
O1	E1	0.781	0.781	0.781	0.612	0.311
O2	0.219	E2	0.311	0.311	0.163	0.163
O3	0.219	0.689	E3	0.781	0.612	0.612
O4	0.219	0.689	0.219	E4	0.781	0.311
O5	0.388	0.837	0.388	0.219	E5	0.612
O6	0.689	0.837	0.388	0.689	0.388	E6
B1	0.388	0.689	0.689	0.689	0.388	0.689
B2	0.689	0.689	0.837	0.930	0.689	0.837
B3	0.930	0.689	0.689	0.930	0.837	0.689
B4	0.689	0.689	0.689	0.689	0.689	0.689
B5	0.930	0.689	0.689	0.837	0.689	0.930
G1	0.689	0.837	0.689	0.689	0.837	0.837
G2	0.388	0.689	0.837	0.689	0.689	0.689
G3	0.689	0.837	0.837	0.689	0.689	0.689
G4	0.837	0.837	0.930	0.689	0.689	0.689
G5	0.689	0.837	0.689	0.930	0.930	0.930
G6	0.689	0.837	0.689	0.837	0.689	0.930
T1	0.689	0.837	0.689	0.689	0.689	0.689
T2	0.689	0.689	0.689	0.837	0.388	0.837
T3	0.837	0.689	0.837	0.219	0.388	0.689
T4	0.837	0.837	0.837	0.930	0.689	0.689
T5	0.689	0.689	0.837	0.689	0.689	0.689

Table 4: Crisp Values for "E_i"

	Developing	Developed
O1	0.612	0.311
O2	0.612	0.612
O3	0.612	0.311
O4	0.311	0.311
O5	0.781	0.612
O6	0.612	0.311
B1	0.612	0.311
B2	0.781	0.311
B3	0.781	0.612
B4	0.311	0.163
B5	0.781	0.612
G1	0.612	0.612
G2	0.781	0.612
G3	0.781	0.781
G4	0.612	0.311
G5	0.781	0.311
G6	0.612	0.612
T1	0.612	0.612
T2	0.612	0.163
T3	0.612	0.163
T4	0.612	0.311
T5	0.781	0.163

6 Conclusion

Index values of specified factors in context with developing and developed nations have been provided in Table 5. The index values of a specific factor depict the degree of its influence on the functioning of PFSC. Higher values of the index represent highly influential factors, while lower values constitute less significant factors. The COVID-19 impact index computed may be utilised to determine the aptness of PFSCs corresponding to different nations in dealing with the global pandemic. Lower index values direct fewer influences and validate that a specific nation may be more suited for the functioning of PFSC. This section incorporates a comprehensive description of the results obtained from the IVIFS-GTMA framework.

6.1 Overall Analysis

From Table 5, it is clear that developing countries are the worst hit due to the COVID-19 pandemic. The index value is 5.91×10^{13} which is very close to the worst value. The coefficient of similarity concerning worst value also proves this, as the C'_{si} value for developing nations is 0.33. On the other hand, developed countries also suffer from this global pandemic but can survive better than developing economies. This fact is proven by the index value, i.e. 3.58×10^{13}, and also by its coefficient of similarity w.r.t. best value, i.e. 0.30. The results justify the substantial gap that advanced technology, enhanced managerial power, increased capital investment strength and proficient workforce create between developed and developing nations.

6.2 Comparison of the Main Factors

The COVID-19 impact index value depicted in Table 5 shows that the operational factors have an index value of 9.902 for developing economies, whereas, for developed economies, it is 6.919. For behavioural factors, the index values for developing and developed nations are 3.777 and 2.244, respectively. Government rules and regulations are critical factors affecting PFSC during this COVID-19 pandemic. Table 5 also depicts the same index values for developing and developed countries, 11.177 and 8.141, respectively. For technological and infrastructural factors, the index values are 3.396 and 1.501 for developing and developed countries, respectively. The lag that shows between developing nations and developed nations concerning the aforementioned operational, behavioural, governmental and technological domains is quite evident. The reasons being, in terms of health and safety, that developed countries have superior infrastructure and a healthier environment than developing countries.

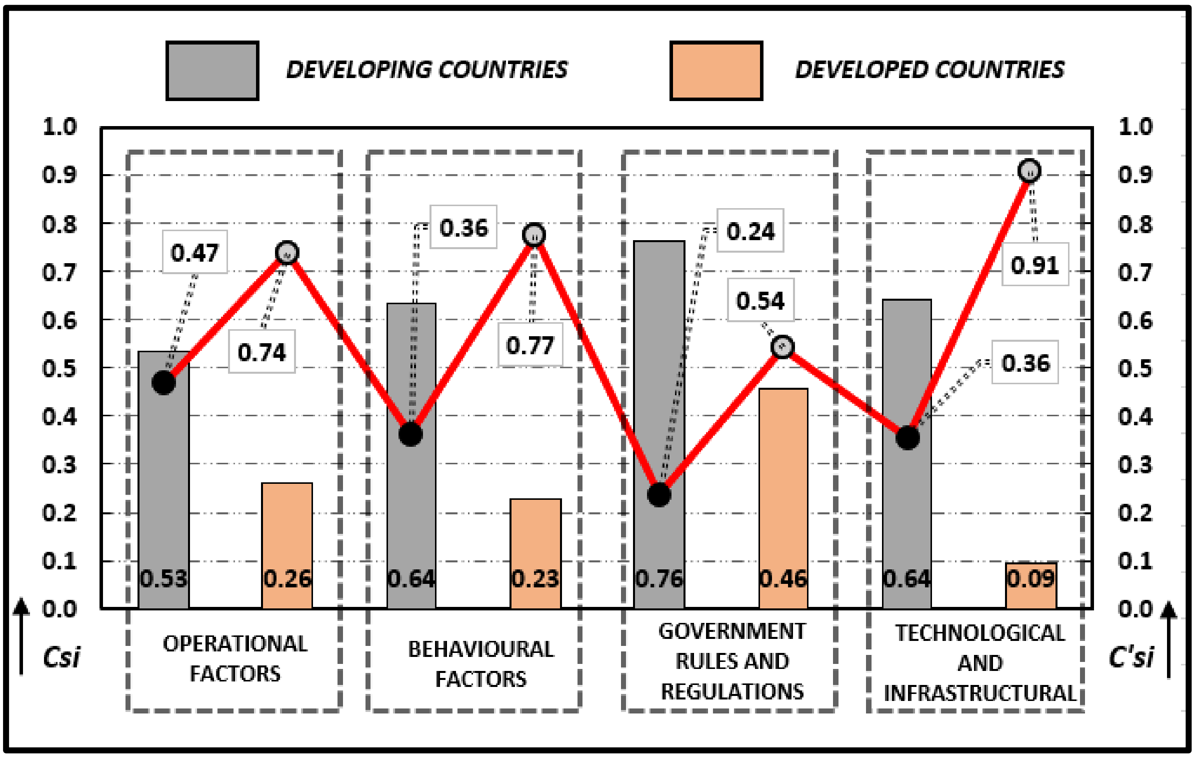
Table 5: Index Values of Various Factors for Developing and Developed Nations

		COVID-19 Impact Index	***Best Value***	***Worst Value***	C_{si}	C'_{si}
Overall Analysis	***Developing***	5.91×10^{13}	1.695×10^{13}	7.96×10^{13}	0.67	0.33
	Developed	3.58×10^{13}			0.30	0.70
O	***Developing***	9.902	4.0878	14.9684	0.534	0.47
	Developed	6.919			0.260	0.74
B	***Developing***	3.777	1.3989	5.1353	0.636	0.36
	Developed	2.244			0.226	0.77
G	***Developing***	11.177	3.5775	13.5189	0.764	0.24
	Developed	8.141			0.459	0.54
T	***Developing***	3.396	1.181	4.6265	0.643	0.36
	Developed	1.501			0.093	0.91

Figure 3 depicts a graphical demonstration of the coefficient of similarity w.r.t best and worst values. This figure helps in comparing the factors – one on one. According to Figure 3, in developing countries, government rules and regulations are the most influencing factor with a

C_{si} value of 0.764. The next most impacting factors are technological and infrastructural (C_{si} = 0.643), followed by behavioural factors having a C_{si} value of 0.636. The least impacting factors are operational factors with a C_{si} value of 0.534. In developed nations, government rules and regulations came in the first position with a C_{si} value of 0.459, whereas operational factors were the second-most impacting factors having a coefficient value of 0.260. The next impacting factors is behavioural factors with a value of 0.226. The least impacting are technological and infrastructural factors with a C_{si} value of 0.093.

Figure 4: Graphical Representation of the Coefficient of Similarity



6.3 Sensitivity Analysis

When human-provided variables are used to build a decision-making index, the outcome is never exact. Numerous questions are raised when studying the data of this research: How much does the weighting of DM preferences affect the index value? Is there any statistical difference due to personal bias? When these weights are altered, how consistent are the results? To counteract uncertainty and provide solutions to such challenges, a sensitivity analysis was conducted. Sensitivity analysis is a popular analytic method for understanding how minor changes in input values impact the stability of a solution (Mukhametzyanov & Pamučar, 2018; Shanker et al., 2021). Chang et al. (2007) illustrated how minor alterations in relative weights may result in significant variances in the component final structure. Since human input is the primary source of decision-making in this study, a sensitivity analysis is required to assess the results. Sensitivity analysis was carried out by varying the weights assigned to the decision-makers. For every instance, one decision-maker's weight is set to "Very Important," whilst the other 24 are set to "Unimportant." In each scenario, the COVID-19 impact index value and C_{si} values for the factors were calculated and compared to the average case. The overall index values for developed and developing nations were also computed using the weightage variations. The results of the sensitivity exercise are summarised in Table 6.

Table 6: Coefficient of Similarity for Factors during Sensitivity Analysis Case

Column1	*Column2*	*Column3*	*Column4*	*Column5*	*Column6*	*Column7*	*Column8*	*Column9*	*Column10*	*Column11*
	Developed					***Developing***				
	Coefficient of Similarity (C_{si})									
	Overall Analysis	***O***	***B***	***G***	***T***	***Overall Analysis***	***O***	***B***	***G***	***T***
Normal	***0.301***	***0.260***	***0.226***	***0.459***	***0.093***	***0.673***	***0.534***	***0.636***	***0.764***	***0.643***
Case 1	0.111	0.091	0.086	0.147	0.032	0.179	0.178	0.175	0.236	0.184
Case 2	0.111	0.092	0.085	0.162	0.034	0.243	0.231	0.240	0.306	0.223
Case 3	0.156	0.027	0.050	0.226	0.007	0.169	0.013	0.272	0.057	0.045
Case 4	0.083	0.068	0.077	0.136	0.027	0.312	0.236	0.217	0.340	0.257
Case 5	0.076	0.081	0.057	0.123	0.028	0.252	0.209	0.219	0.282	0.249
Case 6	0.067	0.019	0.019	0.038	0.022	0.309	0.243	0.107	0.287	0.028
Case 7	0.141	0.121	0.106	0.197	0.041	0.219	0.178	0.219	0.235	0.198
Case 8	0.111	0.099	0.075	0.174	0.029	0.262	0.214	0.185	0.237	0.232
Case 9	0.106	0.103	0.105	0.173	0.043	0.202	0.128	0.153	0.191	0.203
Case 10	0.082	0.074	0.062	0.105	0.025	0.229	0.169	0.226	0.236	0.223
Case 11	0.114	0.096	0.091	0.171	0.035	0.248	0.194	0.241	0.275	0.261
Case 12	0.130	0.094	0.122	0.058	0.029	0.054	0.111	0.040	0.042	0.225
Case 13	0.117	0.121	0.098	0.195	0.037	0.279	0.182	0.217	0.291	0.254
Case 14	0.139	0.112	0.080	0.166	0.043	0.209	0.186	0.164	0.224	0.220
Case 15	0.115	0.073	0.065	0.150	0.030	0.303	0.251	0.285	0.317	0.232
Case 16	0.010	0.049	0.058	0.081	0.018	0.143	0.062	0.033	0.220	0.111
Case 17	0.111	0.092	0.087	0.195	0.034	0.157	0.146	0.169	0.215	0.181
Case 18	0.107	0.103	0.074	0.154	0.032	0.191	0.133	0.184	0.198	0.189
Case 19	0.018	0.016	0.096	0.014	0.003	0.118	0.109	0.202	0.246	0.116
Case 20	0.108	0.094	0.075	0.158	0.038	0.216	0.195	0.210	0.260	0.263
Case 21	0.099	0.107	0.089	0.157	0.035	0.288	0.188	0.251	0.262	0.249
Case 22	0.077	0.067	0.065	0.134	0.031	0.199	0.179	0.166	0.200	0.206
Case 23	0.149	0.116	0.110	0.180	0.038	0.244	0.209	0.230	0.350	0.247
Case 24	0.137	0.103	0.088	0.209	0.039	0.190	0.181	0.200	0.230	0.197
Case 25	0.136	0.102	0.094	0.191	0.036	0.160	0.127	0.161	0.229	0.186

The patterns depicted in Table 6 show consistency in the factor ranking concerning the variations due to the decision makers' weights.

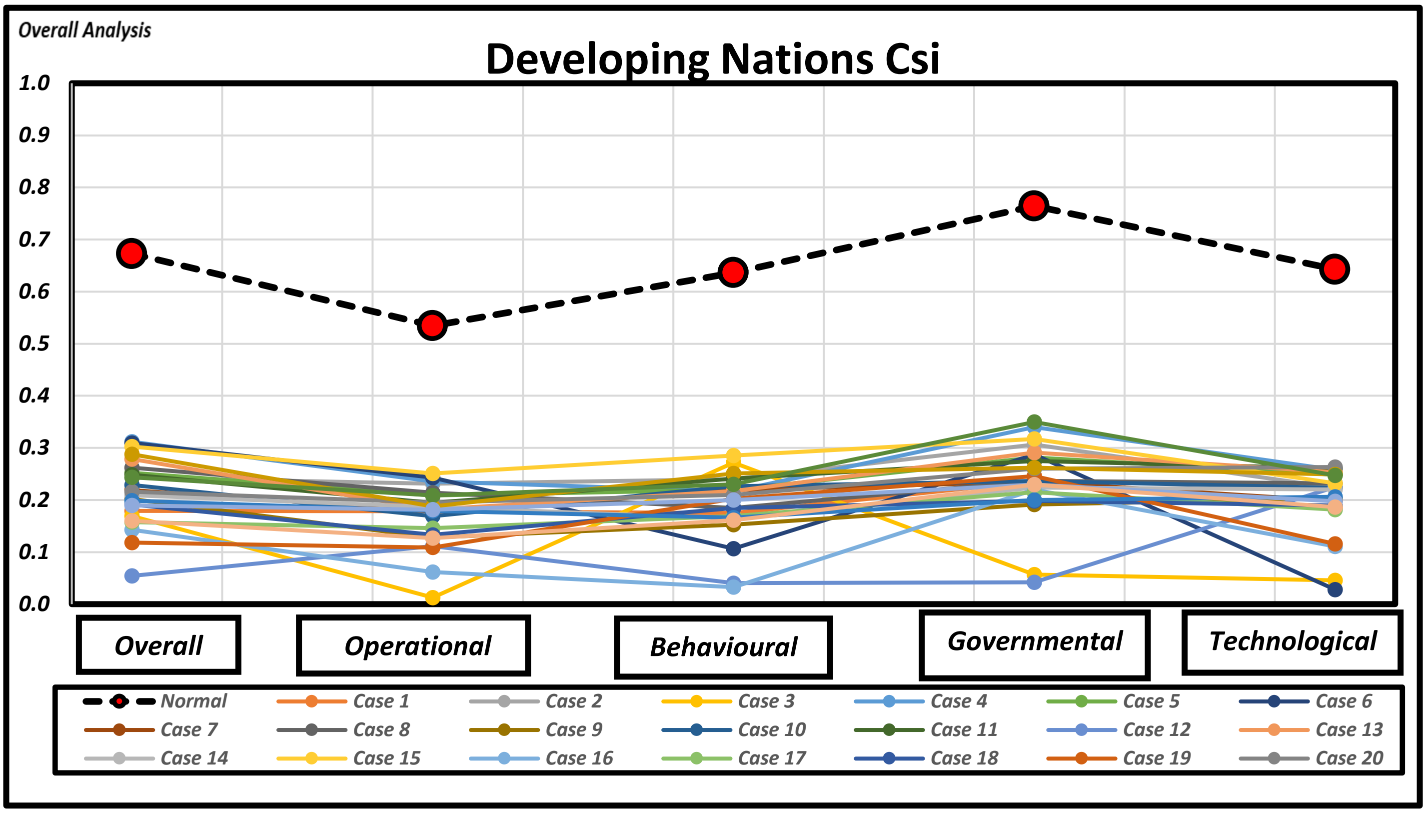


Figure 5: Coefficient of Similarity (C_{si}) of Factors when Changing DM's Weight via Sensitivity Analysis for Developing Nations

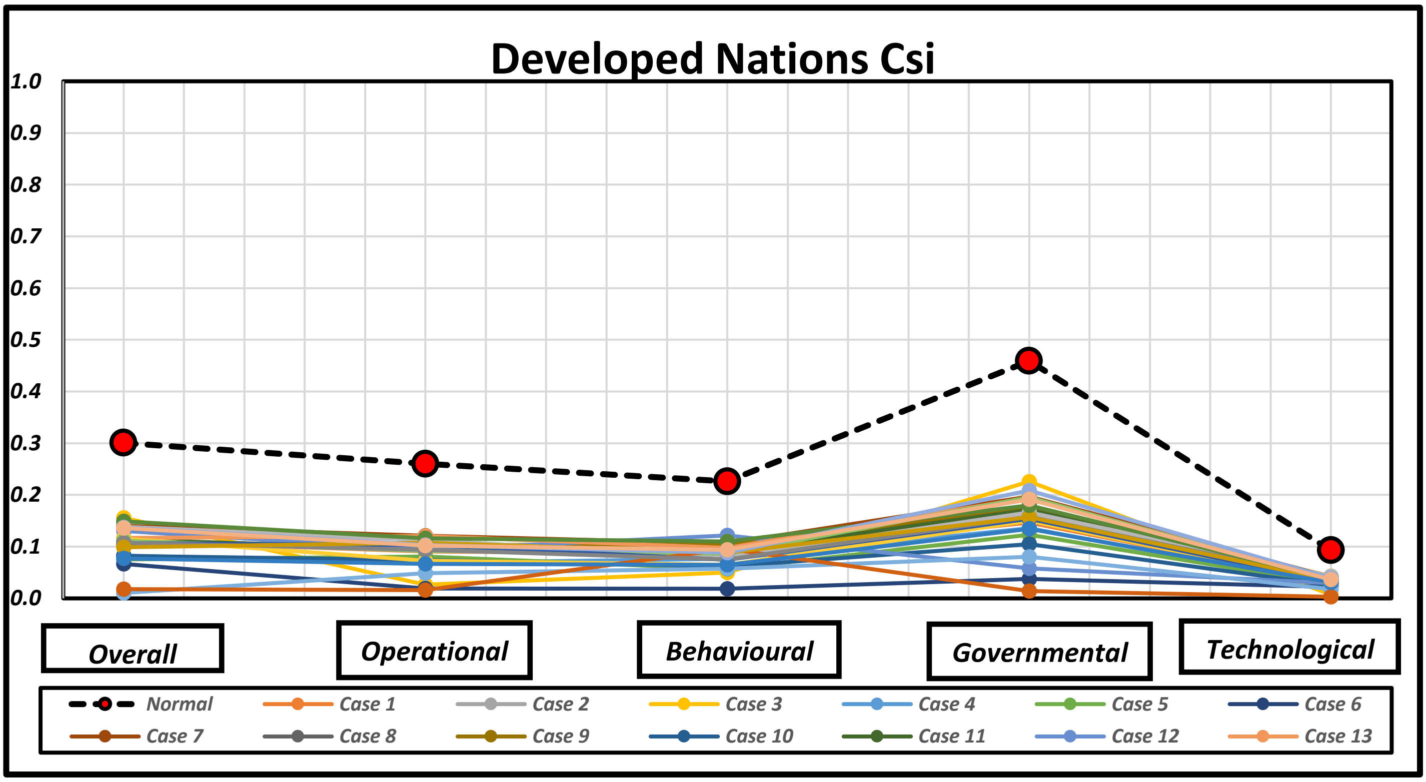


Figure 6: Coefficient of Similarity (C_{si}) of Factors when Changing DM's Weight via Sensitivity Analysis for Developed Nations

The results show that government rules and regulations have the most influence in adversely impacting the PFSCs of both developed and developing nations. This factor is followed by technological and infrastructural factors which specifically worsened the performance of developing nations' PFSCs. Whereas, in developed nations, the next impacting factor is operational, although this is still not significantly effective. The third impacting factor relates to behavioural issues for both developed and developing nations. Whereas, the least influential factor for developing nations is operational, while for developed nations it is technological and infrastructural factors. This ranking of factors according to their influence on developed and developing nations' PFSCs has remained largely consistent throughout the cases. The only cases reflecting variations are case 3, case 6, case 12, case 16 and case 19. Even in these mentioned cases, the ranking order of prominently influential factors remained consistent, only slight changes have been observed. The sensitivity analysis is beneficial to the study's legitimacy in numerous ways. We can argue that observer bias has had little impact on our results by demonstrating that the trends identified in the distribution of key components remain constant, independent of DM weightage.

6.4 Concluding Remarks

The pandemic's effect on various supply chains is a critical and developing research area to provide more in-depth analysis for future strategies. PFSC has become a priority area for policymakers and managers over the last few months, mainly because of its role in the essential item supply chain. An analysis of the impact on PFSC in developed and developing nations during the pandemic is needed to improve the operation of the perishable food sector; this is missing in the currently available literature. To address the above-mentioned concerns, this study has attempted to compare PFSCs of developed and developing nations based on their response to the hurdles encountered during the pandemic. To achieve this, the study recognised 22 potential factors that degraded the performance of the PFSC amidst COVID-19 and classified them into four categories - operational, behavioural, governmental and technological. The manuscript depicted a typical PFSC diagram, highlighting the impact areas of all the recognised factors. A new integrated methodology, IVIFS-GTMA along with the PERMAN algorithm, is utilised in this research to analyse the impact of factors on PFSCs of developing and developed nations. IVIFS served as a scale, best suited to deal with ambiguity. GTMA was exploited to rank and compare PFSCs of developed and developing nations based on the obtained COVID-19 impact index value. The PERMAN algorithm was used in MATLAB to compute the permanent function required to obtain the index value. The results depicted that factors concerning government rules and regulations heavily influence the functioning of PFSCs worldwide. Also, developing nations lag behind developed nations specifically because of the high impact of technological and infrastructural systems; behavioural factors are also important. The study has various research and practical implications that concerned policymakers and managers can make use of. Managers should aim to close the gap between developed and developing nations by carefully examining the technological and infrastructural factors identified.

6.4.1 Implications for Practice

The managers of PFSCs can use the proposed IVIFS-GTMA evaluation framework for enhanced valid analysis of factors, enabling them to draw up strategic plans to boost PFSCs during pandemics. After recording the relevant DM's opinion, a combination of IVIFS into GTMA was utilised to find the relationships and the COVID-19 impact index value of the factors to obtain a strategic framework. Various appreciable administrative visions may be utilised from the methodology used, see Table 5. The managerial aids of this manuscript are:

i. If PFSC legislators and executives hope to achieve high performance in developing countries, it is recommended that they focus on improving the technological and infrastructural factors; a significant difference was seen in this area. Legislators and executives should suggest appropriate technological and infrastructural advances to enhance current provisions.
ii. The findings suggested that government rules and regulations have influenced both developed and developing economies' PFSCs during the pandemic outbreak, indicating that major development and mitigation measures are needed in this field. All types of the economy have been affected.
iii. The results obtained indicate that developing nations significantly lag behind developed nations in the mitigation of operational factors. Henceforth, the factors mentioned under the operational domain need to be carefully analysed and dealt with by management teams.
iv. Behavioural factors are influencing developing nations more adversely compared to developed countries. Behavioural factors correspond to the feelings rooted in the minds of people; this needs to be addressed by policymakers and managers if an effective change is to be made.
v. The significance of recognising the factors impacting PFSCs amidst the pandemic lies in the fact that a problem cannot be cured without knowing the causes behind it. The degradation in PFSC performance during the pandemic demands a careful analysis of the causal factors; this can aid managers in dealing with the problem.
vi. The categorisation of factors is done primarily to make the study more organised and accessible; this will enhance its understandability for the managers responsible.
vii. This study's research findings provide a list of the coefficients of similarity w.r.t best and worst values. Policymakers may utilise this list for the design of effective policies to mitigate the disturbances in PFSC.

6.4.2 Implications for Research

Various implications for research derived from the perishable food supply chain manuscript have been mentioned below in detail.

i. From the theoretical perspective, this paper develops a unique methodology i.e. IVIFS-GTMA using the PERMAN algorithm to analyse the impact of the pandemic on PFSC in developed and developing economies.
ii. In this study, the GTMA technique's linguistic scales were reclassified utilising the IVIFS where data is dealt with in intervals. Moreover, IVIFS acts as an excellent platform to tackle inaccurate and vague data. This study has explored the versatility in the usage of GTMA as well as IVIFS; this is very beneficial for future research.
iii. In addition to this, the proposed technique is reliable as weight is allocated to each DM. Inaccurate, dubious and equivocal data from DMs were dealt with by interval-valued intuitionistic fuzzy numbers. This investigation also utilised the IVIF weighted averaging to total DMs' calculations. Future studies could make use of the above-mentioned investigations.

iv. The present study has accentuated that there is no similar study which analyses the influence of COVID-19 on PFSC in developed and developing nations using these procedures. This study may act as a benchmark for future studies using this hybrid technique.
v. The index framed in this study may help diverse PFSCs check the factors' impact on their operations. The factors may be analysed depending upon their interrelation values and then ranked for a particular perishable food company.

6.4.3 Limitations and Recommendations

This investigation also has a few limitations for future examination. The average operator in gathering DMs' decisions might be additionally improved by utilising new aggregation methods. The concept of a developed and developing nation is not perfect; consequently, because multiple countries were considered for all parts of the spectrum, results have been generalised. Further research might be carried out by studying specific circumstances in a nation utilising the suggested framework and altering the values obtained from decision-makers. Moreover, GTMA restricts the assessment of the impact caused by individual factors on the PFSC.

To carry out an analysis for individual impacting factors, other MCDM techniques may be utilised in the future. MCDM techniques like Analytical Network Process (ANP), Hybrid methodology combining maximum deviation and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), and Choquet integral combined with Decision making trial and evaluation laboratory (DEMATEL) for cause-and-effect analysis can be utilised in future.

Statements and Declarations

Ethics approval and consent to participate: All authors have followed the ethics in the research and gave consent to participate in the research.
Consent for publication: All authors give consent for publication.
Availability of data and material: All the data has been specified in the manuscript.
Competing interests: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.
Research involving Human Participants and/or Animals: No
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Appendix A

Detailed Information about Specialists

Specialists' Domain	***Serial Number***	***Year of Experience***	***Qualification***	***Designation & Job Description***	
Logistics and Supply Chain Academician	1	16	PhD	Professor	Supply chain management
	2	12	PhD	Associate Professor	Production and logistics management
	3	10	PhD	Assistant Professor	Food supply chain management
	4	14	PhD	Associate Professor	Operations Management
	5	17	PhD	Professor	Supply chain management
	6	13	PhD	Associate Professor	Industrial Management
	7	13	PhD	Associate Professor	Production and Operations Management
	8	15	PhD	Professor	Industrial Engineering
Perishable Product Companies Specialists	9	13	Master degree in Engineering	Enterprise service manager	Inventory Planning
	10	14	Master degree in Engineering	Supply chain functional analyst	Supply chain functioning

	11	13	MBA	Operations manager	Resource and operations control
	12	12	Master in Science	Supply Chain analyst	Predictive Analysis
	13	13	Master of Technology	Demand Planner	Demand Forecasting
	14	10	MBA	Logistics Manager	Logistics Management
	15	11	MBA	Operation Manager	Operations management
	16	12	MBA	Outbound Logistics Manager	Transportation Management
	17	14	Master of Technology	Distribution Network Planning	Route Optimisation
	18	15	Master of Technology	Warehouse Manager	Industrial Engineering
	19	10	MBA	3PL manager	Logistics service management
	20	11	MBA	Pricing Executive	Differential Pricing Planning
	21	10	MBA	Director of Operations	Production and operations management
	22	13	Master of Science	Supply Chain Executive	Simulation forecasting
	23	12	Master of Science	Industrial Engineer	Industrial Engineering
	24	11	MBA	Service Provider Consultant	Logistics Service Provider Management
	25	13	MBA	Distribution Manager	Distribution and network designing