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Research Article

Factors Related to Industry 4.0 and Industry 5.0 Capabilities and Their Influence on Supply Chain Resilience and Flexibility

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ABSTRACT

Supply chain resilience and flexibility are among the most critical dynamic capabilities for surviving in the modern world of uncertainties and risks arising from unexpected dynamics in global supply chain routes and hubs. Resilience may be viewed as the supply chain capability enabling resistance and withstanding power against disruptions and flexibility defines the modern supply chain capability to adjust to the disruptions to respond to market dynamics and keep the businesses running. Industry 4.0 and Industry 5.0 technologies capabilities can enable the supply chain capabilities of resilience and flexibility positively by offering powerful technology-driven enablers. This research studied the technology-driven enablers and their contributions to the supply chain resilience and flexibility. There were five Industry 4.0 and two Industry 5.0 technology enablers found from the literature review to create an initial model. The model was projected to Fuzzy Interpretive Structural Modeling (FISM) method in which, eighteen experts were selected working in the industrial cities in the Indian states of UP and in MP in logistics engineering having good insight about Industry 4.0 and Industry 5.0 technologies. The experts were engaged through a focus group discussion in which, a structured questionnaire was presented to them for building Structural Self-Interaction Matrix (SSIM) by each expert. The responses collected from each expert were analysed through the FISM steps. The output showed a hierarchical model with four levels of driving and dependence powers. The IIoT, fog computing, cloud manufacturing, big data analytics, and blockchains were found to be having root driving powers in the model. These five variables are technology-driven enablers of Industry 4.0, which were found to be driving the two technology-driven enablers of Industry 5.0: smart robotics and human-centric artificial intelligence. The Industry 5.0 variables were found to be driving supply chain flexibility, which in turn had driving power over supply chain resilience. The practical validity of this hierarchical model was discussed in detail at the end of this article in the context of a flexible and smart manufacturing and logistics system connected with digitalised supply chains. The notions of flexibility and resilience were also discussed in a cellular manufacturing system that can be configured and re-configured quickly as per the demand dynamics.

Keywords: Industry 4.0, Industry 5.0, Logistics Engineering, Digital Transformation and Integration, Resilience in Supply Chain, Flexibility in Supply Chain.

1. Introduction

Supply chain resilience and flexibility may require core enhancements at the root of modern logistics engineering. The older technologies may have induced capabilities for smooth operations of supply chains but causing certain boundaries and constraints making change management a difficult challenge (Gupta et al., 2021). Rapid adjustments and changes are required when the demands become highly complex and dynamic in the marketplaces (Abeysekara and Wang, 2019). Further, supply chains also need to be resilient systematically and structurally to withstand disruptions in the ongoing supply chain operations (Adobor and McMullen, 2018; Ambulkar, Blackhurst, and Grawe, 2015). Managing disruptions have been handled traditionally through business continuity management, which can be enhanced by capabilities supporting rapid changes and adjustments (Crichton, Ramsay, and Kelly, 2009; Denyer, 2017; Steen, Haug, and Patriaca, 2023). Hence, supply chain resilience is related to the capabilities enabling flexibility.

As empirically established in the recent studies (as reviewed in the next section), Industry 4.0 and Industry 5.0 technologies can enable the capabilities supporting supply chain flexibility and hence the resilience.

This research investigates the common capabilities enabled by Industry 4.0 and Industry 5.0 technologies influencing supply chain resilience and flexibility.

The following research questions were investigated in this research:

(a) What are the key capabilities with mutual interrelationships related to Industry 4.0 and Industry 5.0 technologies?

(b) How the key capabilities of Industry 4.0 and Industry 5.0 technologies affect the Resilience and Flexibility of supply chains?

The following highlights were achieved in this research:

(a) Industry 4.0 and Industry 5.0 frameworks with their technologies and their corresponding capabilities relevant to the flexibility and resilience in the modern Supply Chain and its supporting Logistics Engineering have been reviewed from literature;

(b) Experts' opinions and related rankings related to the effects of Industry 4.0 and Industry 5.0 technological capabilities on supply chain resilience and flexibility following the focus group method among selected eighteen experts in logistics engineering having good insight about Industry 4.0 and Industry 5.0 technologies; the experts were selected from industrial cities in the Indian states of Madhya Pradesh (MP) and Uttar Pradesh (UP) in India;

(c) The experts' rankings were investigated for driving and dependency powers using the A fuzzy interpretive structural model (FISM) method; the focus group discussion method was followed to evolve a structural construct showing the Industry 4.0 and Industry 5.0 technological capabilities and their affects on resilience and flexibility of supply chain management and its supporting logistics engineering was achieved;

(d) A justification on what FISM could achieve in arriving at the finalized relationships and what could be the next steps for future research;

In the next section, the Industry 4.0 and Industry 5.0 technologies and their resulting capabilities for logistics engineering are studied with the help of review of literature.

2. Industry 4.0 and Industry 5.0 technological capabilities for Logistics engineering

Industry 4.0 and Industry 5.0 technologies essentially provide the necessary digital transformation of logistics engineering for supporting the supply chain processes with new dynamic flexible capabilities (Bag, Gupta, and Luo, 2020; Chung, Kim, and Lee, 2018; Conner, 2018). Digital transformation can transform the vision and governance of an organisation and also develop a culture of informed and smart decision-making (He et al., 2023). Hence, culture, skills, and training of employees are key factors in addition to implementing the digitalisation technologies as in the Industry 4.0 and Industry 5.0 frameworks (Nkomo and Kalisz, 2023). The next section presents a wider review of the people aspects as they are linked with resilience and flexibility of the organisations. Continuing this section, a review of Industry 4.0 and Industry 5.0 technological capabilities is presented as the following.

The Industry 4.0 and Industry 5.0 frameworks for logistics engineering ride on two core technological innovations: digitalisation at the end computing and the cloud computing (Conner, 2018; Daniluk and Holtkamp, 2015; Holtkamp, 2015; Qu et al., 2016; Wolf and Rahn, 2015). The logistics systems closer to the end customer interfacing on cloud computing are termed as the "logistics mall" (Daniluk and Holtkamp, 2015; Holtkamp, 2015) and the ones closer to the manufacturers are called "cloud manufacturing" (Lim, Xiong, and Wang, 2021; Qu et al., 2016; Zhong et al., 2016). The digitalisation is carried out using Industrial Internet of Things (IIoT) (Conner, 2018). The digitalisation domain incorporates ordering, inventory, production, and delivery logistics are digitalized for effective integration of information combining the data (Sakhri, 2024). The combined data is used for generating analytical charts in real time that enables quick decision making thus ensuring the right products produced and delivered to the right customers at the right times. The digitalisation-enabled logistics enhancements realised in logistics are speed, flexibility, connectivity, real-time intelligence, transparency, cost-effectiveness, proactive approach, and sustainability (Christopher, 2023; Sakhri, 2024). Such enhancements in logistics support the operational capabilities of a synchronous supply chain.

The digitalisation of logistics engineering using the Industry 4.0 and Industry 5.0 technologies comprises of Cyber Physical Systems (CPS), Industrial Internet of Things (IIoT), Cloud Computing, Big Data Analytics (BDA), Artificial Intelligence (AI), Blockchain (BC), Unmanned Aerial Vehicles (UAV), and mobile computing (MC) (Najafi and Atighi,

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2024; Sakhri, 2024; Vaseei, 2024). The IIoT is at the root of digitalisation as it is attached to the logistics equipment and machines for providing an interface for data collection and communications. Machines and equipment fitted with sensors of variables crucial to process operations and the IIoT for consolidating and transmission of sensory data are called the cyber physical systems (CPS). At the receiving side of data, cloud computing platform is commissioned for hosting the BDA, AI, and the BC. The BDA, AI, and the BC have advanced higher layer roles in modern digitalised logistics engineering. As these systems are deployed on the cloud computing, they constitute a remote management system conducting two tasks: data analytics and decision-making. In modern logistics, all the software systems traditionally deployed in self-managed and controlled data centres are deployed on cloud computing (Wolf and Rahn, 2015). The BDA and AI capabilities are integrated with the running operating platforms such as enterprise resources planning (ERP), manufacturing execution systems (MES), materials requirements planning (MRP), and warehouse and transport management systems (WTMS) (Michlowicz, 2021). Hence, the analytics are also integrated with them producing the operating curves for the desired operations: transportation, logistics systems, warehousing, and production.

Modern manufacturing, logistics, and supply chain operations are controlled through cloud-hosted operating platforms that collectively constitute the cloud manufacturing system (Abdmeziem, Tandjaoui, Romdhani, 2016; Bartodziej, 2017; Ghomi, Rahmani, Qader, 2019; Lim, Xiong, and Wang, 2021; Qu et al., 2016). In cloud manufacturing, the logistics engineering applications are primarily deployed on cloud computing with some support from edge computing. In industrial systems interfaced with cloud manufacturing, the industrial programmable logic controllers are transformed into cyber physical devices capable of collecting and consolidating data from the running processes in edge computing servers and transmitting the data to cloud computing systems. The data transmission to cloud computing and data stored in smart contracts blockchains are facilitated through application programmable interfaces created in the backend cloud-based database layers forming the building blocks of big data systems (Barenji and Montreuil, 2022; Bartodziej, 2017; Henzel & Herzwurm, 2018; Unal et al., 2021). The physical layer comprising of industrial machines and power systems and their controllers need to be fully integrated with the digitalised programmable logic controllers such that all the process execution data can be transmitted to the cloud-based big data systems. The data is used by the logistics monitoring and control software on the cloud computing accessible through field edge devices for accepting commands and sending status reports. The data is also used to generate as-is as well as analytical reporting. At the highest layer, artificial intelligence is used for predictive analytics. The entire framework is shown in Figure 1.

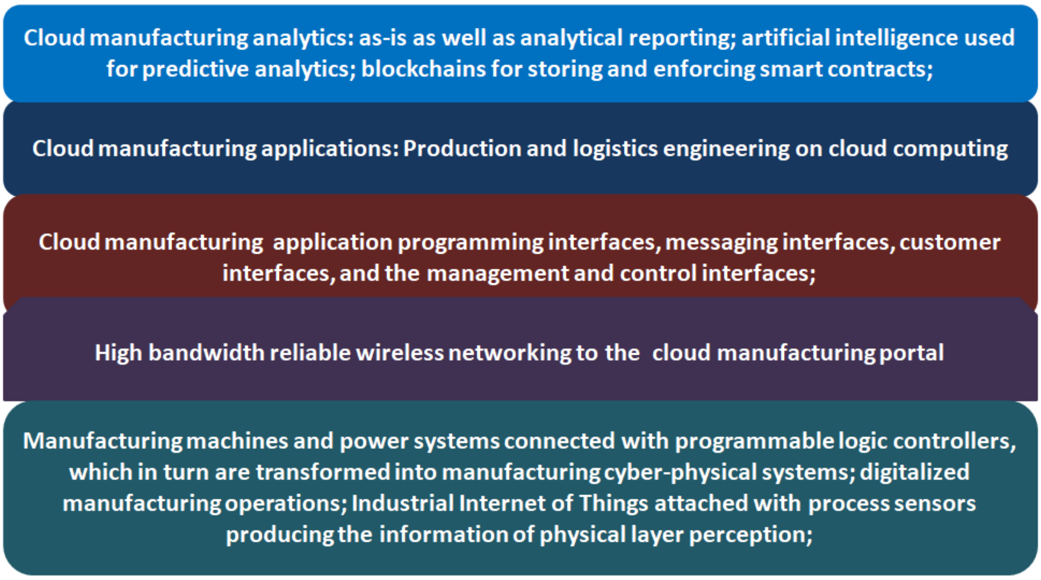

Figure 1: Digitalisation and cloud manufacturing (based on theoretical review of Barenji and Montreuil, 2022; Bartodziej, 2017; Culot, 2021; Lim, Xiong, and Wang, 2021; Samad et al., 2023; Santhi and Muthuswamy, 2022; Unal et al., 2021)

The framework shown in Figure 1 is based on Industry 4.0 technologies serving as the foundation for Industry 5.0 technologies (Rahmaty, 2024). The Industry 4.0 capabilities are distributed among the five layers shown in the Figure 1 and are integrated through vertical integration of a technology stack (Bartodziej, 2017; Culot, 2021). Industry 5.0 framework is built on the foundation of these technologies albeit at a much higher maturity level ensuring a "human centric" approach allowing human operators to monitor and control a large swarm of distributed machines and robots following commands from artificial intelligence (Boz and Pinto, 2024; Nozari, 2024). One may view the system as several artificial intelligence systems following the commands of human beings but making their own low-level operational decisions. The robotics and machines deployed are smart and multi-tasking capable following the instructions issued by the artificial intelligence systems. With such a possibility, the technological capabilities of Industry 4.0 and Industry 5.0 framework for logistics engineering are reviewed the following:

(a) Industrial Internet of Things (interfacing physical and digital layers) (Bartodziej, 2017; Lim, Xiong, and Wang, 2021; Qu et al., 2016): The IIoT is at the core of digitalisation in the Industry 4.0 era. It can collect data directly from the running industrial processes as it can be established as the layer above the programmable logic controllers. It serves as the primary interfacing between the physical and virtual realms as it can build and continuously update the perception of the physical layer in the digital layer.

(b) Fog Computing (consolidating physical layer data) (Elaraby, 2021; Kaya, Paksoy, and Garza-Reyes, 2021; Tarneberg, 2019): Fog (edge) computing is deployed for networking all the IIoT-enabled data sources in Industry 4.0 processes to transfer their data streams to the edge servers closest to them for consolidating their data. The edge servers transmit the consolidated IIoT data to big data systems on the cloud computing.

(c) Cloud manufacturing (for smart and distributed manufacturing systems) (Abdmeziem, Tandjaoui, Romdhani, 2016; Bartodziej, 2017; Lim, Xiong, and Wang, 2021; Qu et al., 2016; Unal et al., 2021): Cloud manufacturing is a smart and distributed manufacturing Industry 4.0 framework in which, the manufacturing monitoring and control processes are distributed to several physical manufacturing plants controlled by software systems running on partially cloud computing and partially on the fog computing systems. The manufacturing machines and robots are also transformed to smart devices using the cyber-physical and IIoT digitalization. The machines and robots are assigned some form of "awareness" using machine learning abilities embedded in them and controlled by centralized artificial intelligence on the cloud computing.

(d) Big data analytics (analysis of multi-layer multi-location information collected from IIoT) (Najafi and Atighi, 2024; Sakhri, 2024; Vaseei, 2024): Big data is characterized by velocity (rapid data transmissions), variety (supporting hundreds of variables), volume (massive scales of data storage), and veracity (relevance, correctness and accuracy of data), and value (usefulness of the data). Big data analytics consolidates multi-location multi-layered multi-variable data for deep visualization and advanced statistical and machine learning enabled analysis. Big data analytics is the backbone of all the modern logistics capabilities projected by the academic researchers in Industry 4.0 literature.

(e) Smart contracts in blockchains (Barenji and Montreuil, 2022; Kayikci, 2021; Samad et al., 2023; Santhi and Muthuswamy, 2022; Tiwari et al., 2023; Vaseei, 2024): Blockchains can store encrypted smart contracts broken in blocks integrated through hash functions. Smart contracts are transparent and irrefutable. They ensure formalizing involvement, engagement, and accountability of logistics actors in Industry 4.0 cloud manufacturing.

(f) Smart multi-tasking robotics (Alim and Kesen, 2021; Woschank, Rauch, and Zsifkovits, 2020): Smart multi-tasking robots are controlled through machine learning embedded in their firmware interacting with cloud-hosted artificial intelligence for conducting multi-tasking with cognitive, environmental, and neighborhood awareness. They can operate in large swarms conducting multitasking operational tasks following human-generated commands to the cloud-hosted artificial intelligence. They are the core innovations in Industry 5.0.

(g) Artificial intelligence (Human-Centric) (Demir and Paksoy, 2021; DHL, 2018; Liu et al., 2023; Oh, 2019; Woschank, Rauch, and Zsifkovits, 2020): Operational level artificial intelligence evolved in the Industry 4.0 paradigm. At this level, automation and predictive analytics are the key capabilities developed in logistics helping in relatively accurate planning and execution. However, handling swarms of robots and machines requires human-centric artificial intelligence, which is a feature proposed in the Industry 5.0 paradigm. Human centricity can allow a few individual managing massive scale productions, logistics and supply chain operations. Innovations like automatic driving trucks and connected vehicles can add to the capabilities centered at human centricity.

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The influence of modern capabilities induced by Industry 4.0 and 5.0 technologies relevant to logistics engineering can have profound effects on supply chain flexibility and resilience. Digital transformation can influence flexibility and resilience and their mutual relationship in logistics. The capabilities of Industry 4.0 and industry 5.0 technologies may have varying influences on flexibility and resilience depending upon the industrial setting and its business environment. The next section presents specific review of literature about organisational flexibility and resilience achievable through digital transformation.

3. Supply chain flexibility, resilience, and their interrelationship through digital transformation

The primary objective of logistics engineering is to orchestrate large number of assets for meeting the production and supply chain operations objective functions (targets and goals) (Christopher, 2022; Harrison, van Hoek, and Skipworth, 2015; Stadtler, 2015). The orchestration of logistics assets is carried out using the advanced planning and scheduling system, which was conceptualised to make optimised allocation of resources to meet the volumes and timelines at the lowest possible costs. Logistics engineering performance has been measured traditionally through its ability to respond flexibly to the market and demand dynamics. Increasing the degrees of freedom allowed in a highly constrained operational framework having tightly coupled bounds has always been the dream of logistics engineers. This was possible through dynamic designs (such as cellular manufacturing, vendor-managed inventory, and collaborative forecasting, planning, and replenishments). The bottlenecks were felt in the older technological capabilities causing hard coded processes in the ERP, MES, MRP, and WTMS systems.

Supply chain integration of processes and resources have been advocated for gaining flexibilities in procurements, operations, timelines, costs, materials, resources, and other influencing variables (Chaudhuri, Boer, and Taran, 2018; Irfan, Wang, and Akhtar, 2020; Li et al., 2020; Ralston and Blackhurst, 2020; Shukor et al., 2021). Through integration, the logistics operations managers gain wider choices to make their planning, scheduling, and routing with increasing flexibility. Multi-party collaboration improves flexibility in the variables of interest for logistics operational efficiency. Industry 4.0 and Industry 5.0 technological capabilities for digital integration of processes and resources are viewed as modern enhancements essential to the technology support infrastructure of logistics engineering. To deliver flexibilities in logistics and supply chain, the desired technological flexibilities are essential (Han, Wang, and Naim, 2017). Digital transformation ensures that all the four dimensions of flexibility (people cultures and skills, organisational processes, technologies, and organisational strategy and direction) can be covered (Nkomo and Kalisz, 2023). Flexibility achieved through multi-dimensional integration can ensure resilience against supply chain disruptions (Shekarian, Nooraie, and Parast, 2020). The absorptive capacity and rapid learning by an organisation are key determinants for surviving in a dynamic business environment (Rojo et al., 2018). Industry 4.0 becomes a positive enabler for flexibility and resilience because it helps in collecting and analysing data about the metrics that matter and enable smart and self-adjusting systems (Ralston and Blackhurst, 2020).

In the next section, the methodology planned and executed for the primary research part of this study is explained.

4. Research Methodology:

An interpretive philosophical approach with inductive learning approach was followed in this research to execute a qualitative research methodology called fuzzy interpretive structural modelling (FISM) (Saunders, Lewis, and Thornhill, 2009). The FISM helps in evolving new structural models for theory building by evolving a structural construct based on the rankings of relationships provided by subject matter experts of the subject being studied. Eighteen logistics engineering specialists studying the role of Industry 4.0 and 5.0 technologies for the future of their industrial domains in the Indian states of MP and UP were selected for the FISM. The expert profiles are presented as the following:

Experts 1 to 8: The Experts 1 to 8 are experienced in the processes following digital manufacturing. They have been operating digitalised supervisory control systems communicating with digital programmable logic controllers having analogue to digital converters for channelizing the industrial signals generated by process sensors. They primarily use Intranet communications with IPv6 protocol but have proposed plans to implement Internet communication channels using MQTT (message queuing telemetry transport) protocol for integrating control systems of multiple manufacturing plants of the same company.

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Experts 9 to 12: These experts work for data centres in digitalised manufacturing companies. They are already working on Industry 4.0 pilot systems with big data at the core. They are also testing artificial intelligence for automation. They have knowledge about the future of human centricity following Industry 5.0 framework of technologies.

Experts: 13 to 16: These experts are consultant hired by the sampled digitalised manufacturing plants for their Industry 4.0 and Industry 5.0 migration plans for cloud-based manufacturing systems and integrating all their production houses.

Experts 17 and 18: These experts are the owners of the sampled manufacturing plants digitalised.

The focus group method was adopted in this research. It involves conducting an in-depth group discussion with experts selected related to the research domain and requesting them to provide data from their practical fields (Yin, 2011). As explained in the book by Yin (2011), focus group results in expert knowledge provided by experts with very deep insight. This research used structured questionnaire for building Structural Self-Interaction Matrix (SSIM) by each expert. Hence, the responses collected in this research are measurable. There were 18 SSIMs built each separately by the 18 experts. The final SSIM was compiled by calculating MODE of each cells of the individual SSIMs. This research followed the FISM steps (as explained by Khatwani et al., 2015; Mohanty and Shankar, 2017; Tyagi, Sharma, and Shukla, 2019) as the following:

Step 1: Identifying the factors for which, the experts shall generate their individual SSIMs. The factors in this study are technological capabilities of Industry 4 + 5 frameworks influencing the supply chain flexibility and resilience.

Step 2: The experts are requested to generate their SSIMs. In the SSIM, the row headers are presented as "i" and headers are presented as "j". The influences of "i" factor variables on "j" factor variables are forward influences and the same of "j" factor variables on "i" are reverse influencers. There may be bidirectional influences, as well. The relationships by the experts may be defined as V (i → j), A (j → i), X (i ←→ j), or O (N; no relationships). The strengths are recorded within brackets for all the relationships. Fundamentally, there are five strength levels presented as perfect (P), strong (S), moderate (M), and weak (W), and no strength (N). The absolute influence of unity may be defined as the sixth level. Normally, it shall be the self-influencing strength of a variable but experts may decide on absolute mutual relationships, as well.

Step 3: The SSIMs collected from the experts comprise of linguistic equivalents of relationships. The unidirectional and bi-directional relationships are defined following the Table 1 (Das, Azmi, and James, 2020; Tyagi, Sharma, and Shukla, 2019). Some examples as per Table 1 are: V (P): a perfect forward relationship, A (S): a strong reverse relationship, and X (S, P): A bidirectional relationship having strong in the forward direction and perfect in the reverse direction. Following the same conventions, there can be six unidirectional and nine bidirectional relationships. No relationship can be only one denoted by O (N).

Step 4: In this step, the SSIM is transformed by replacing the linguistic values by their corresponding fuzzy values. The Table 1 shows the five levels of strengths and their fuzzy values. The fuzzy values have been taken as per the five levels defined in the research by Tyagi, Sharma, and Shukla, (2019). As the fuzzy numbers are triangular, they have been represented as three numbers within brackets. Triangular Fuzzy behaviour indicates variation of the value of a factor variable among three numbers at a specific level on a scale.

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Table 1: The levels and names of the scale with their corresponding triangular fuzzy values

Level	Name	Linguistic Term	Triangular Fuzzy Value
5	Perfect	P	(0.75, 1, 1)
4	Strong	S	(0.5, 0.75, 1)
3	Moderate	M	(0.25, 0.5, 0.75)
2	Weak	W	(0, 0.25, 0.5)
1	No influence	N	(0, 0, 0.25)

The Equation (1) presents the triangular fuzzy number $\mu_A(X)$ defined in the research studies by Elizabeth and Sujatha (2013) and their later study in Elizabeth and Sujatha (2015). Figure 1 shows the plotting of the triangular fuzzy number.

$$\mu_A(X) = \begin{cases} 0 & if\ X \leq a\ or\ X \geq c \\ \frac{x-a}{b-a} & if\ a \leq X \leq b \\ \frac{c-X}{c-b} & if\ b \leq X \leq c \end{cases} \quad \text{Equation (1)}$$

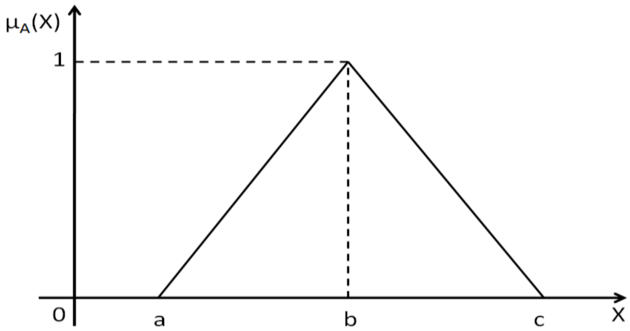

Figure 2: Plotting of the Triangular fuzzy number using the magnitude method by Elizabeth and Sujatha (2013) and Elizabeth and Sujatha (2015)

Step 5: In this step, the SSIM is transformed (again) by entering the defuzzified values of each of the fuzzy values. There are several methods for defuzzification of triangular fuzzy numbers. In this research, the "the formula of magnitude measure" proposed by Elizabeth and Sujatha (2013) and Elizabeth and Sujatha (2015) was used. The formula is replicated in Equation (2):

Magnitude of $\mu_A(X) = \frac{a+7b+c}{12}$ Equation (2)

By applying the formula shown in the Equation (2), the defuzzified magnitudes of the triangular fuzzy numbers are tabulated in the Table 2:

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Table 2: Defuzzification table (Elizabeth and Sujatha, 2013; Elizabeth and Sujatha, 2015):

Level No.	Level's name	Linguistic Term	Triangular Fuzzy Value	Defuzzified value using magnitude method
5	Perfect relationship	P	(0.75, 1, 1)	0.729
4	Strong relationship	S	(0.5, 0.75, 1)	0.5625
3	Moderate relationship	M	(0.25, 0.5, 0.75)	0.375
2	Weak relationship	W	(0, 0.25, 0.5)	0.1875
1	No relationship	N	(0, 0, 0.25)	0.0208

Step 6: In this step, the defuzzified data of all the SSIMs generated by the experts is consolidated in an aggregated defuzzified SSIM table (Khatwani et al., 2014). For this purpose the MODE method (value having highest frequency in the data set) was followed (Mohanty and Shankar, 2017). MODE is the most preferred method of aggregating SSIMs of all experts in the FISM literature (Das et al., 2020) because it represents the majority voting approach (Jain and Soni, 2019).

Step 7: After aggregating the SSIMs in a final SSIM, all defuzzified values are converted back to their linguistic equivalents. This SSIM represents the combined opinion of the experts following the majority voting approach.

Step 8: The linguistic equivalents helped in arriving at the initial reachability matrix. In this step, only the relationships perceived as significant for the research are retained and shown as unity after the steps of fuzzification, defuzzification and aggregation have been completed. The relationships retained were the unidirectional relationships with Perfect and Strong strength levels or the bidirectional relationships having at least one of these strength levels. All other relationships were dropped out of the SSIM because they were perceived as insignificant for the research. This reachability matrix is called "initial" as it shows only the direct relationships.

Step 9: The next step was to create the final reachability matrix, which involves direct and indirect relationships shown for all possibilities at the perfect and strong levels. The direct relationships have been taken from the initial reachability matrix and the indirect relationships are extracted from the transitivity relationships such that all missing gaps can be filled. These relationships are marked as "*" to differentiate them from the direct relationships.

Step 10: Conduct the MICMAC analysis: MICMAC (abbreviation for Matrix impact-cross multiplication applied to classification) represents plotting of driving and dependence powers of all the factor variables in four quadrants called: autonomous, dependent, independent, and linkage. In this plotting, some of the factor variables may be pushed to the edge of independent variables (factor variables rarely influenced by any other in the model) and the edge of dependent variables (variables that rarely influence any other variable). Some of the variables are caught in between that can be both influencing and influenced. The driving power represents the "level of independence" of a factor variable and the dependence power represents the "level of dependence" of an influenced variable. In real world, there is no variable with absolute independence and absolute dependence. Hence, the driving and dependency powers are estimated within a group of variables forming a boundary of a construct studied in a specific research.

Step 11: The level partitioning table is generated for analysing it. This step shows the level partitions showing the reachability, antecedents, and intersections.

Step 12: In this step, the driver and dependence powers were shown numerically in the conical matrix. It also shows the variables with transitivity power, called the mediators or moderators depending upon their natures (that is, they exist to cause the other relationships in the model).

Step 13: In this step, the path diagram was drawn showing the relationships and the levels of the variables. This is different from the diagraph as it only shows the direct relationships. The diagraph shows all the direct, indirect, and transient relationships those are not useful for this research.

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Step 14: The finalised FISM model was drawn as the research output. The theoretical reflections of the finalised FISM model were discussed by linking back with literature review outcomes. The statistical validity of the FISM model can be studied further in the future studies following advanced multivariate methods.

In FISM, there is no statistical validity conducted using multivariate methods as it is a structured estimation of collective opinions of the subject matter experts conducted primarily using matrices. Hence, the FISM may be followed to create a construct for further statistical analysis using advanced methods. It may be considered as a good qualitative method with initial quantitative indicators. It may be noted that different experts have varying opinions, as is reflected in this study as well. Hence, using FISM for validation will require much larger sampling (like 100 or more experts). However, FISM becomes highly tedious at such large sample sizes. Hence, this research used FISM in a small sample size of 18 respondents only. Empirical confirmation shall require deductive approach such as the advanced multivariate statistical analysis methods that are globally accepted to be generating empirically established results (Sekaran, 2003). The sample sizes in such methods are much larger than the FISM method. The next section presents the results of FISM and discussion on them.

5. Results and Discussion:

The steps explained in the previous section were executed to achieve the intermediate FISM results and the finalised FISM model. This section presents and discusses the results of the steps taken. The first step of determining the factor variables to be studied was carried out with the help of literature review presented in the Sections 2 and 3. The factor variables learnt from the literature review are shown in the Table 3.

Table 3: Variables derived from literature review

Factors	Names
F1	Industrial Internet Of Things for interfacing physical and digital layers
F2	Fog Computing for consolidating physical layer data
F3	Cloud Manufacturing for smart and distributed manufacturing systems
F4	Big Data Analytics for analysis of multi-layer multi-location information collected from IIoT
F5	Smart Contracts In Blockchains
F6	Smart Multi-tasking Robotics
F7	Human-Centric Artificial Intelligence
F8	Supply chain flexibility
F9	Supply chain resilience

The FISM steps helped in learning about the interrelationships among the factor variables F 1to F9. To achieve this, the factor variables shown in the Table 3 were discussed with the team of experts' team in a focus group discussion session. The experts were coded from E1 to E18. The SSIM matrix templates were shared with each of the experts and were requested to assign all the relationships an appropriate coding from the list comprising the codes in the SSIM matrix template. These codes were described in the previous section. The same description was shared with the panel of experts. The experts were given a time of 30 minutes to fill in their respective SSIM matrix templates. The templates were entered in eighteen tabs named as E1 to E18 (for easy mapping with the experts) of a shared Excel sheet and each expert was requested to fill in their respective tabs online. Majority of the experts could fill the template in less than 30 minutes. After filling the templates, the experts were requested to view responses made by the others in the focus group. Thereafter, the experts were requested to make any changes they deem fit in their response sheets if they feel as necessary. In this research, the experts did not make any changes.

The SSIMs were constructed in separate of an Excel sheet. Their transformed matrices with fuzzifed and defuzzified values were also entered in the same respective tabs based on their individual responses. In the excel sheet, a nineteenth tab was created for consolidation in which, the mode of the responses were calculated and provided in the

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SSIM aggregated. The Table 4 below shows the finalized aggregated SSIM comprising of the modes of defuzzified responses made by the experts.

Table 4: Mode values of the defuzzified responses as consolidated in the final SSIM

Variables	F1	F2	F3	F4	F5	F6	F7	F8	F9
F1	1	0.729	0.729	0.729	0.729	0.729	0.729	0.729	0.729
F2	0.375	1	0.729	0.729	0.729	0.729	0.729	0.729	0.729
F3	0.729	0.0208	1	0.729	0.729	0.729	0.729	0.729	0.729
F4	0.729	0.0208	0.0208	1	0.375	0.375	0.0208	0.729	0.729
F5	0.729	0.0208	0.0208	0.375	1	0.375	0.375	0.729	0.729
F6	0.0208	0.0208	0.0208	0.5625	0.375	1	0.375	0.729	0.729
F7	0.0208	0.0208	0.0208	0.0208	0.375	0.375	1	0.729	0.729
F8	0.0208	0.0208	0.0208	0.0208	0.0208	0.0208	0.0208	1	0.729
F9	0.0208	0.0208	0.0208	0.0208	0.0208	0.0208	0.0208	0.0208	1

The defuzzified values in the Table 4 show strong preference for the perfect relationship (P value as 0.729) and no relationships (N value as 0.0208). There is only one strong relationship (S value as 0.5625) and a few moderate relationships (M value as 0.375) There are no weak relationships (W value as 0.1875). The corresponding fuzzy values of the finalised SSIM are as shown in Table 5.

Table 5: SSIM with Fuzzy values

Variables	F1	F2	F3	F4	F5	F6	F7	F8	F9
F1	1	(0.75, 1, 1)	(0.75, 1, 1)	(0.75, 1, 1)	(0.75, 1, 1)	(0.75, 1, 1)	(0.75, 1, 1)	(0.75, 1, 1)	(0.75, 1, 1)
F2	(0.25, 0.5, 0.75)	1	(0.75, 1, 1)	(0.75, 1, 1)	(0.75, 1, 1)	(0.75, 1, 1)	(0.75, 1, 1)	(0.75, 1, 1)	(0.75, 1, 1)
F3	(0.75, 1, 1)	(0, 0, 0.25)	1	(0.75, 1, 1)	(0.75, 1, 1)	(0.75, 1, 1)	(0.75, 1, 1)	(0.75, 1, 1)	(0.75, 1, 1)
F4	(0.75, 1, 1)	(0, 0, 0.25)	(0, 0, 0.25)	1	(0.25, 0.5, 0.75)	(0.25, 0.5, 0.75)	(0, 0, 0.25)	(0.75, 1, 1)	(0.75, 1, 1)
F5	(0.75, 1, 1)	(0, 0, 0.25)	(0, 0, 0.25)	(0.25, 0.5, 0.75)	1	(0.25, 0.5, 0.75)	(0.25, 0.5, 0.75)	(0.75, 1, 1)	(0.75, 1, 1)
F6	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0.5, 0.75, 1)	(0.25, 0.5, 0.75)	1	(0.25, 0.5, 0.75)	(0.75, 1, 1)	(0.75, 1, 1)
F7	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0.25, 0.5, 0.75)	(0.25, 0.5, 0.75)	1	(0.75, 1, 1)	(0.75, 1, 1)
F8	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	1	(0.75, 1, 1)
F9	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	(0, 0, 0.25)	1

Finally, the finalised SSIM with linguistic equivalents of defuzzified values are presented in the table serving as the final SSIM outcome. This outcome is shown in the Table 6:

Table 5: SSIM with Linguistic Equivalents

Variables	F1	F2	F3	F4	F5	F6	F7	F8	F9
F1	1	X(P, M)	X(P, P)	X(P, P)	X(P, P)	V(P)	V(P)	V(P)	V(P)
F2		1	V(P)	V(P)	V(P)	V(P)	V(P)	V(P)	V(P)
F3			1	V(P)	V(P)	V(P)	V(P)	V(P)	V(P)
F4				1	X(M, M)	X(M, S)	O(N)	V(P)	V(P)
F5					1	X(M, M)	X(M, M)	V(P)	V(P)
F6						1	X(M, M)	V(P)	V(P)
F7							1	V(P)	V(P)
F8								1	V(P)
F9									1

From this point forward, the relationships X (W, M), X (M, M), X (M, W), V (W), V (M), O (N) were dropped as they undesirable levels of strengths and the others were retained. Ahmad and Ayman (2021) provided a web-enabled tool that was used to generate the initial reachability matrix in which, the retained relationships were entered as X (if bidirectional) and V (if unidirectional in forward direction). There were no reverse unidirectional relationships. The relationships dropped were treated as "O (no relationship)" in subsequent steps. The inputs made to the web-enabled tool by Ahmad and Ayman (2021) is shown in the Figure 3 below. The variable names have been shortened than those shown in the Table 3 for simplifying the display.

Figure 3: Relationships entered in the tool by Ahmad and Ayman (2021) after eliminating the undesirable ones

In the SSIMs allocated to the experts, their opinions were entered on the relationships as well as about their strengths. This gesture helped in rejecting the weak relationships and retaining the unidirectional relationships of P and S strengths only and the bidirectional relationships having at least unidirectional P or S. Generally, every relationship may be having some influence on the construct. However, considering weak or moderate relationships will make the model complex and difficult to evaluate. Hence, to build a bigger and prominent picture, the weak or moderate relationships may be eliminated.

The tool by Ahmad and Ayman (2021) operates automatically once the button names "Calculate ISM Results" shown in the screenshot of Figure 3 is pressed. All the remaining reports are generated automatically. The relationships retained are all shown as "1" indicating existence of a relationship (but not indicating absolute strength of the relationship).
The initial reachability matrix is presented in the next table (Table 6):

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Table 6: Initial Reachability Matrix

Reachability Matrix(RM)

Variables	1	2	3	4	5	6	7	8	9	Driving Power
F1:Industrial Internet Of Things	1	1	1	1	1	1	1	1	1	9
F2:Fog Computing	1	1	1	1	1	1	1	1	1	9
F3:Cloud Manufacturing	1	0	1	1	1	1	1	1	1	8
F4:Big Data Analytics	1	0	0	1	0	0	0	1	1	4
F5:Smart Contracts in Blockchains	1	0	0	0	1	0	0	1	1	4
F6:Smart Multi-tasking Robotics	0	0	0	0	0	1	0	1	1	3
F7:Human-Centric Artificial Intelligence	0	0	0	0	0	0	1	1	1	3
F8:Supply chain flexibility	0	0	0	0	0	0	0	1	1	2
F9:Supply chain resilience	0	0	0	0	0	0	0	0	1	1
Dependence Power	5	2	3	4	4	4	4	8	9	

The direct relationships among the factors and their driving and dependence powers are evident in the initial reachability matrix. As evident in Table 6, F1 and F2 have the highest driving powers followed by F3. F4 to F8 have moderate driving powers and F9 has the least driving power. However, these are not the final driving and dependence powers. The final values of these powers are estimated in the final reachability matrix adding the indirect relationships. It is shown in the Table 8. The powers have changed after accounting for the indirect relationships, as well. In the final reachability matrix, the driving powers of F1 to F5 are now at 9, the driving powers of F6 and F7 and at 3, the driving power of F8 is at 2, and the driving power of F9 is at 1. This matrix also shows that variables F1 to F5 have moderate dependence powers at 5, F6 and F7 have dependence powers at 6, F8 has a dependence power of 8, and F9 has the dependence power at 9. The final matrix of dependencies is shown in Table 7 where relationships with the "*" identification are transient or indirect relationships and others are direct relationships.

Table 7: Final Reachability Matrix

Final Reachability Matrix(FRM)

Variables	1	2	3	4	5	6	7	8	9	Driving Power
F1:Industrial Internet Of Things	1	1	1	1	1	1	1	1	1	9
F2:Fog Computing	1	1	1	1	1	1	1	1	1	9
F3:Cloud Manufacturing	1	1*	1	1	1	1	1	1	1	9
F4:Big Data Analytics	1	1*	1*	1	1*	1*	1*	1	1	9
F5:Smart Contracts in Blockchains	1	1*	1*	1*	1	1*	1*	1	1	9
F6:Smart Multi-tasking Robotics	0	0	0	0	0	1	0	1	1	3
F7:Human-Centric Artificial Intelligence	0	0	0	0	0	0	1	1	1	3
F8:Supply chain flexibility	0	0	0	0	0	0	0	1	1	2
F9:Supply chain resilience	0	0	0	0	0	0	0	0	1	1
Dependence Power	5	5	5	5	5	6	6	8	9	

The Matrix impact-cross multiplication applied to classification, abbreviated as MICMAC, chart shows the distribution of driving, dependency, and transient (linkage) statuses of all the variables. The MICMAC plot is shown in Figure 4 generated by the tool by Ahmed and Ayman (2021).

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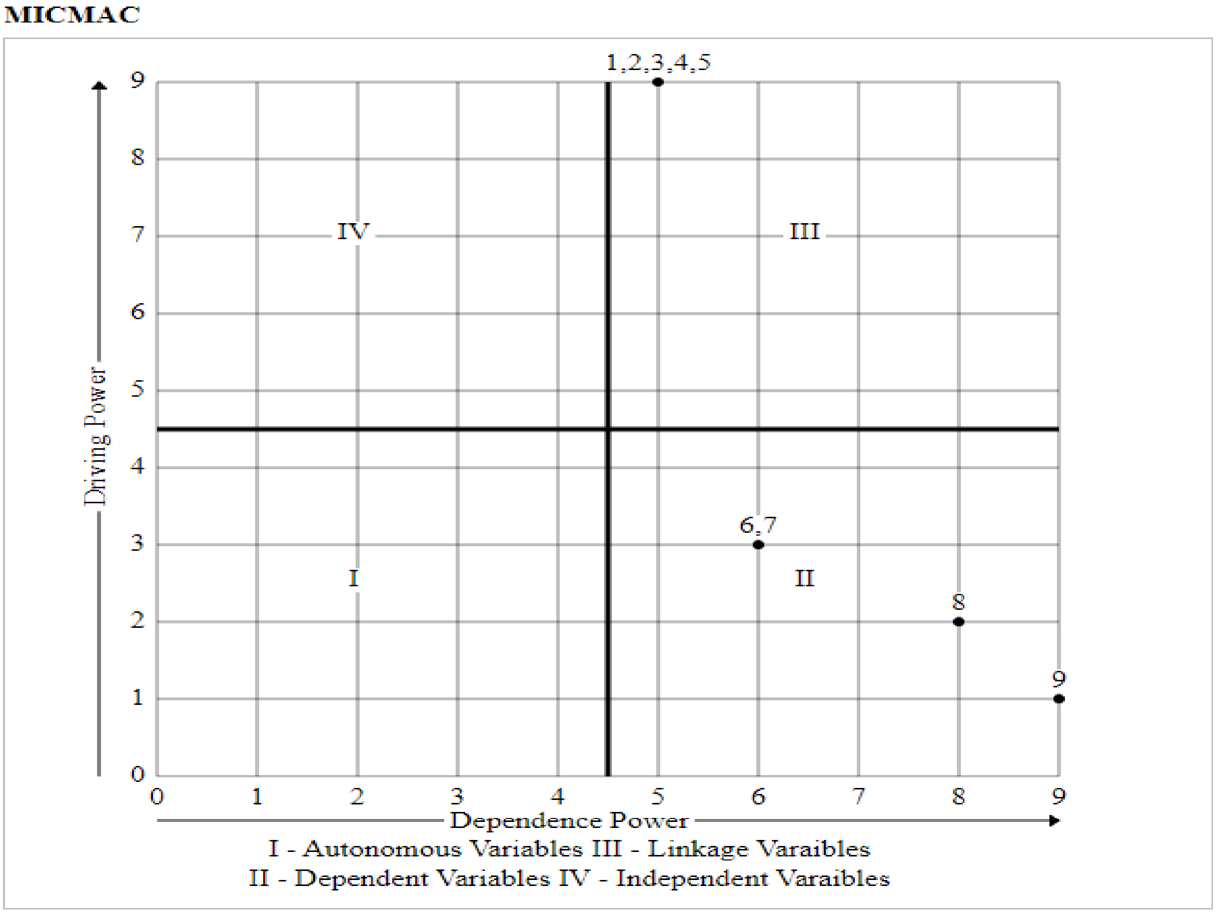

Figure 4: MICMAC chart

The MICMAC chart in the Figure 4 presents the factor variables F1 to F5 as having equal driving powers than the factor variables F6 to F9. The factor variables F1 to F5 have the same driving power of 9 and the dependence power of 5 indicating their mutual predecessor – successor relationships, as well. The predecessor – successor relationships are shown in the level partitioning table in Table 8. The variables having the lowest driving powers are F8 and F9. F8 has a driving power of 2 and F9 has a driving power of 1. Hence, F8 is a predecessor of F9 indicating a causal relationship even at the far end of dependencies plotting in the MICMAC diagram as shown in the Table 8. The F6 and F7 variables have moderate driving power of 3 each. Such a construct may be considered as hierarchical as is evident in the final FISM model.

Table 8: Level Partitioning Matrix

Level Partitioning(LP)

Elements(Mi)	Reachability Set R(Mi)	Antecedent Set A(Ni)	Intersection Set R(Mi)∩A(Ni)	Level
1	1, 2, 3, 4, 5,	1, 2, 3, 4, 5,	1, 2, 3, 4, 5,	4
2	1, 2, 3, 4, 5,	1, 2, 3, 4, 5,	1, 2, 3, 4, 5,	4
3	1, 2, 3, 4, 5,	1, 2, 3, 4, 5,	1, 2, 3, 4, 5,	4
4	1, 2, 3, 4, 5,	1, 2, 3, 4, 5,	1, 2, 3, 4, 5,	4
5	1, 2, 3, 4, 5,	1, 2, 3, 4, 5,	1, 2, 3, 4, 5,	4
6	6,	1, 2, 3, 4, 5, 6,	6,	3
7	7,	1, 2, 3, 4, 5, 7,	7,	3
8	8,	1, 2, 3, 4, 5, 6, 7, 8,	8,	2
9	9,	1, 2, 3, 4, 5, 6, 7, 8, 9,	9,	1

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All the antecedents, intersections, and reachability relationships at four levels of partitioning are presented in the level partitioning matrix (Table 8). The partitions are formed based on the driving/dependency powers of the factor variables and the antecedents, intersections, and reachability relationships represent the relationships' chaining that has been traced in the final traceability matrix. The level partitioning matrix shows the hierarchical structure of the relationships with four levels in the hierarchy. The variables F1 to F5 are at the level 4 because of their highest driving power of 9 in the model. The variables F6 and F7 are at the level 3 because of their moderate driving power of 3. The variable F8 is at the level 2 because of its driving power of 2 and the variable F9 is at level 1 because of its driving power of 1.

Table 9: Conical Matrix

Conical Matrix(CM)

Variables	9	8	6	7	1	2	3	4	5	Driving Power	Level
9	1	0	0	0	0	0	0	0	0	1	1
8	1	1	0	0	0	0	0	0	0	2	2
6	1	1	1	0	0	0	0	0	0	3	3
7	1	1	0	1	0	0	0	0	0	3	3
1	1	1	1	1	1	1	1	1	1	9	4
2	1	1	1	1	1	1	1	1	1	9	4
3	1	1	1	1	1	1*	1	1	1	9	4
4	1	1	1*	1*	1	1*	1*	1	1*	9	4
5	1	1	1*	1*	1	1*	1*	1*	1	9	4
Dependence Power	9	8	6	6	5	5	5	5	5		
Level	1	2	3	3	4	4	4	4	4		

In the Table 9 the final determination the reachability and the relationships' powers (driving and dependence) are shown. It is called the conical matrix. It is the summary table of the FISM output. The picture of the output model is shown in Figure 5 to be discussed theoretically. The reachability relationships defining the dependency powers of the variables F1 to F5 create complexities for further theoretical analysis. Hence, they were removed from the final model discussed theoretically in this study. The finalised model, shown in Figure 6, has been created by eliminating all the transient (indirect) relationships. This means that all mutual antecedents and reachability relations within the levels were dropped. The finalised model presented in Figure 6 is the FISM output for theoretical analysis.

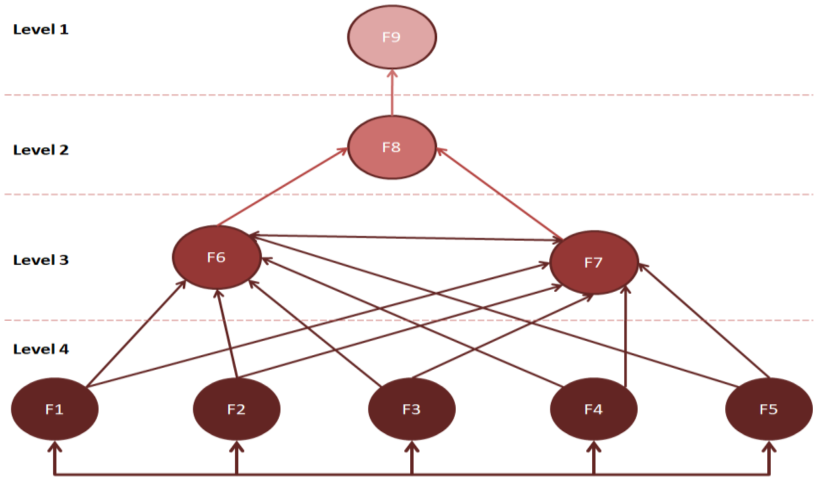

Figure 5: Construct created in Smart ISM application by Ahmed and Ayman (2021) [redrawn in colour]

It may be noted that both Figures 5 and 6 have an intrinsic colour coding in which, the darkness of colours represent increase in driving powers prevailing at those levels. Further, it may be noted that the interrelationships within the

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four levels have been eliminated in the Figure 6. Only the inter-level relationships have been retained for the theoretical model. This has been done to simplify the model for theoretical analysis of hierarchical integration and not integrations within the levels that may add too many relationships for multivariate analysis. The multivariate methods if used in future may recover some of those relationships if they support higher model fitment when tested for multivariate statistical validity.

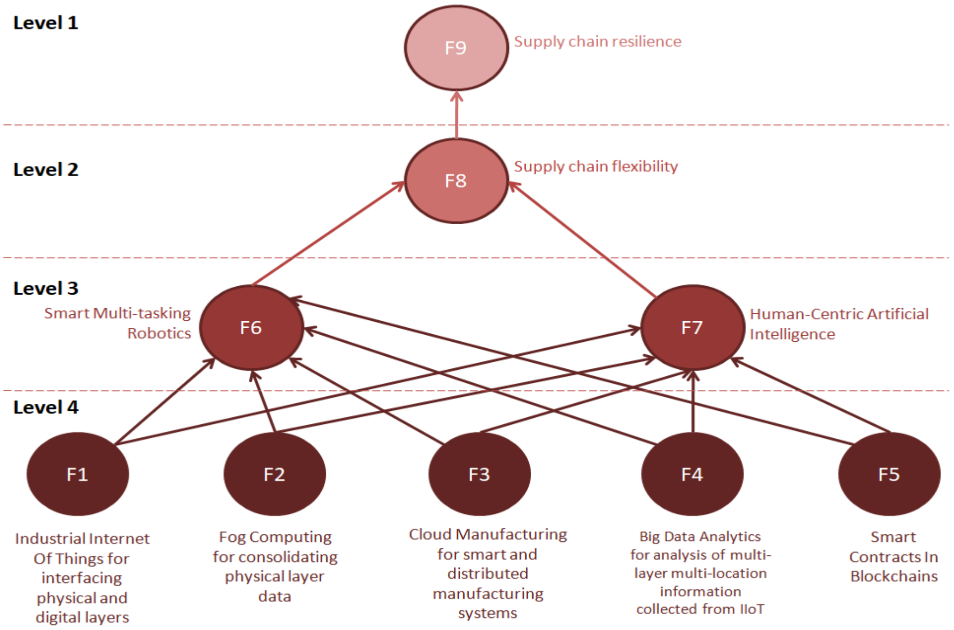

Figure 6: Final Model created in Smart ISM application by Ahmed and Ayman (2021) [Redrawn in colour]

Hence, the final model of this research is the Figure 6 that is now analysed theoretically to justify the relationships learnt through the FISM efforts. Al though not proven for empirical validity by FISM, the relationships carry empirical significance that may motivate future researchers to study them further and attempt to establish their empirical validity. The first aspect to keep in mind is that the finalised model has four levels in a hierarchy. This reflects a hierarchical existence within the technologies studied in the Industry 4.0 and Industry 5.0 frameworks. The factors F1 to F5 form the foundation for both Industry 4 and Industry 5 frameworks. They enable the effectiveness of factors F6 and F7. The factors F1 to F7 collectively influence the dependent variables, but again there is a hierarchy between the two as F8 influences the F9.

The factors F1 to F5 have the highest driving powers and also have mutual dependencies. This is because while they form the foundation of the Industry 4.0 framework, they are also influencing mutually. They may be having varying driving powers mutually. For example, a CPU may have higher driving power than memory and hard disk drive. However, from value generation perspective the full computer is considered. Similarly, the full Industry 4.0 system comprising the factors F1 to F5 drives the value generation irrespective of the mutual driving powers of the individual components. Thus, all the components are equally essential. The roles of F1 to F5 are well defined in the literature reviewed in this study (such as, Abdmeziem, Tandjaoui, Romdhani, 2016; Bartodziej, 2017; Ghomi, Rahmani, Qader, 2019; Lim, Xiong, and Wang, 2021; Michlowicz, 2021; Najafi and Atighi, 2024; Sakhri, 2024; Vaseei, 2024). The digital transformation carried out by these components is analysed in a simple language from the perspective of the authors as described below:

(a) IIoT for interfacing the physical and digital layers: The IIoT sensors should be deployed in every active system in digitally transformed manufacturing, logistics, and supply chain setting, such as machines, robots, production controllers, internal and external transport systems, pickup, retrieval, and pallet transfer systems, etc. IIoT connections can free up all such devices from any cabling attachments thus making them freely configurable as cellular/modular manufacturing system. Manufacturing assembly lines and all support and delivery systems can be customised dynamically as per the orders received by the organisation.

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(b) Fog computing for consolidating the physical layer data: Fog computing is the wireless network of all IIoT-enabled manufacturing, logistics, and supply chain setting. Devices and their controllers can communicate seamlessly on local wireless networks, such as Wi-Fi and 5G networks. 5G may be more preferred as it supports several localised cells with uplinks and downlinks at high bandwidths and data speeds. The concept of dynamic cellular/modular manufacturing can be effectively enabled by the fog computing networks deployed in operational settings.
(c) Cloud manufacturing for smart and distributed manufacturing systems: While fog computing can facilitate dynamic capabilities within localised premises (such as production plants, warehouses, and depots), cloud computing can integrate all such facilities to form a complete digitalised supply chain. As described by multiple research studies (Lim, Xiong, and Wang, 2021; Qu et al., 2016; Zhong et al., 2016), integrated manufacturing and their supporting facilities through cloud computing forms a cloud manufacturing system.
(d) Big data analytics for multi-layer multi-location information collection: As reviewed, big data analytics may be viewed as a technology for integrating the real time events happening in multiple locations for synchronising their operations. For example, machines integrated as assembly line in one location may be viewed in real time for preparing their deliveries in a warehouse at another location. The customers may be provided real time visualisation of all the activities happening for their deliveries to offer them better trust and transparency.
(e) Smart contracts using blockchains: Blockchains may be used to tie up all client deliveries with smart contracts for fixing accountabilities. As smart contracts can get direct updates on execution activities (Barenji and Montreuil, 2022; Bartodziej, 2017; Henzel & Herzwurm, 2018; Unal et al., 2021), customers may be provided interfaces to view execution of their orders in real time.
With these five technologies in place, the Industry 5.0 capabilities of smart robotics and human-centric AI can be activated. Smart robotics take commands from artificial intelligence but conduct their localised operations smartly by remaining process, environment, and cognitively aware, and operate individually as well as in groups (Boz and Pinto, 2024; Najafi and Atighi, 2024; Nozari, 2024; Sakhri, 2024; Vaseei, 2024). Smart rbots may be tasked to complete several sequences of process steps autonomously without needing human intervention. The human operators no longer talk to the robots for issuing commands; instead they command the artificial intelligence that in turn commands the smart robots. This is the human-centric concept of artificial intelligence. With these layers in place, the supply chain operations can have flexibility given the modularity and cellular assembly structure and smart robots in action capable of making quick self changes and operational environment changes. With Industry 4.0 and 5.0 capabilities in place, flexibility is possible in production, plant operations, interplant logistics, plant to warehousing/distribution logistics, retail logistics, and in the customer delivery logistics. Riding on the flexibilities is resilience that protects the business operations from unforeseen events. Flexibility in supply chain can ensure rapid readjustments when a supply chain risk is evident. The human centric AI concept can allow human operators to make quick and valuable readjustments based on the situational awareness applying their experiences and wisdom.

6. Conclusion

The Industry 4.0 and Industry 5.0 capabilities in a cloud manufacturing setting were reviewed in this research. The cloud manufacturing stack studied in this research revealed a mechanism of physical perception in a production, logistics, and supply chain setting getting digitalised and transmitted to the digital world from where, the physical world can be monitored and controlled through the digitalised perception layer. The exact replica of the digitalised perception can be formed in digital twins with the help of big data systems that receive data continuously from the digitalised perception layer. The synchronous information exchange between the perception layer and the digital twin representation of the physical layer can be used for invoking smart capabilities in machines, robots, and other systems. If the information exchange is fully controlled by AI, then human centric AI operations can be carried out. On simple human commands, AI can execute highly complex operations. The digitalisation of the physical layer ensures that all machines and robots can be controlled in bigger groups with high levels of modularity. The orchestration among various agencies owning the machines, robots, and other systems can be executed through smart contracts in a blockchain. Thus, the digitalised framework is friendly to flexible/cellular manufacturing and logistics operations. With flexibility, resilience can be built into the system as the human operators can have flexibility to moderate or modify the operational specifications based on demand changes by instructing the smart robots. For example, a running modular assembly line in the cellular construct may be changed or completely reorganised by the robots on the instructions of their human instructors. The foundational factors of this level of maturity comprises the IIoTs, fog computing, cloud manufacturing, and big data analytics, and blockchains. This was the final output of the FISM method followed in this research.

References:

[1] Abeysekara, N., Wang, H., Kuruppuarachchi, D. 2019. Effect of supply-chain resilience on firm performance and competitive advantage: A study of the Sri Lankan apparel industry. Business Process Management Journal, 25 (7): 1673-1695 [Emerald]

[2] Adobor, H. and McMullen, R. S. 2018. Supply chain resilience: a dynamic and multidimensional approach. The International Journal of Logistics Management, 29 (4): 1451-1471 [Emerald]

[3] Ahmad, N. And Ayman, Q. 2021. "SmartISM: Implementation And Assessment of Interpretive Structural Modeling" Sustainability, 13 (16): 8801 [MDPI]

[4] Ambulkar, S., Blackhurst, J., Grawe, S. 2015. Firm's resilience to supply chain disruptions: Scale development and empirical examination. Journal of Operations Management, 33–34: 111–122 [Elsevier]

[5] Carlsson, O. 2017. Engineering of IoT Automation Systems. Published PHD Thesis in Industrial Electronics, Lulea University of Technology.

[6] Chaudhuri, A. and Boer, H. and Taran, Y. 2018. Supply chain integration, risk management and manufacturing ?exibility. International journal of operations and production management, 38 (3): 690-712 [Emerald]

[7] Christopher, M. 2023. Logistics and Supply Chain Management, 6th edition [London: NY: Financial Times Publishing]

[8] Crichton, M. T., Ramsay, C. G., Kelly, T. 2009. Enhancing Organizational Resilience Through Emergency Planning: Learnings from Cross-Sectoral Lessons. Journal of Contingencies and Crisis Management, 17 (1): 24-37 [Blackwell]

[9] Culot, G. 2021. Industry 4.0 and the future of manufacturing: Theoretical base and empirical analyses. Published PHD Thesis, [University of Udine]

[10] Denyer, D. 2017. Organizational Resilience: A summary of academic evidence, business insights and new thinking. Joint Academic Research by BSI and Cranfield University, 1-54 [Cranfield University and British Standards Institution]

[11] Elizabeth, S. and Sujatha, L. 2013. Critical Path Problem under Fuzzy Environment. International Journal of Computer Applications, 75 (1): 7-11.

[12] Elizabeth, S. and Sujatha, L. 2015. Project Scheduling Method Using Triangular Intuitionistic Fuzzy Numbers and Triangular Fuzzy Numbers. Applied Mathematical Sciences, 9 (4): 185-198 [Hikari]

[13] Gupta, S., Modgil, S., Meissonierc, R., Dwivedi, Y. K. 2021. Artificial Intelligence and Information System Resilience to cope with Supply Chain Disruption. IEEE Transactions on Engineering Management, 71: 10496-10506 [IEEE]

[14] Han, J. H., Wang, Y., Naim, M. 2017. Reconceptualization of information technology flexibility for supply chain management: An empirical study. International Journal of Production Economics, 187: 196–215 [Elsevier]

[15] He, Z., Huang, H., Choi, H., Biligihan, A. 2023. Building organizational resilience with digital transformation. Journal of Service Management, 34 (1): 147-171 [Emerald]

[16] Irfan, M., Wang, M., Akhtar, N. 2020. Enabling supply chain agility through process integration and supply flexibility. Asia Pacific Journal of Marketing and Logistics, 32 (2): 519-547 [Emerald]

[17] Jain, V. and Soni, V. K. 2019. Modeling and analysis of FMS performance variables by fuzzy TISM. Journal of Modelling in Management, 14 (1): 2-30 [Emerald]

[18] Khatwani, G., Singh, S. P., Trivedi, A., Chauhan, A. 2015. Fuzzy-TISM: A Fuzzy Extension of TISM for Group Decision Making. Global Journal of Flexible Systems Management, 16: 97-112 [Springer]

[19] Li, C., Wong, C. W. Y., Yang, C., Shang, K., Lirn, T. 2020. Value of supply chain resilience: roles of culture, flexibility, and integration. International Journal of Physical Distribution & Logistics Management, 50 (1): 80-100 [Emerald]

[20] Lim, M., Xiong, W. and Wang, C. 2021. Cloud manufacturing architecture: a critical.analysis of its development, characteristics and.future agenda to support its.adoption, Industrial Management and Data Systems, 121 (10): 2143-2180 [Emerald]

[21] Mohanty, M. and Shankar, R. 2017. Modelling uncertainty in sustainable integrated logistics using Fuzzy-TISM. Transportation Research Part D, 53: 471–491 [Elsevier]

[22] Najafi, E. and Atighi, I. 2024. Employing AI in the Sustainability of Smart Commerce and Supply Chain. In H. Nozari (Ed.) Information Logistics for Organizational Empowerment and Effective Supply Chain management. 139-149 [PA, USA: IGI Global]

[23] Nkomo, L. and Kalisz, D. 2023. Establishing organisational resilience through developing a strategic framework for digital transformation. Digital Transformation and Society, 2 (4): 403-426 [Emerald]

[24] Ralston, P. and Blackhurst, J. 2020. Industry 4.0 and resilience in the supply chain: a driver of capability enhancement or capability loss?, International Journal of Production Research, 58 (16): 5006-5019 [Taylor & Francis]

[25] Rojo, A., Stevenson, M., Llorens-Montes, J., Perez-Arostegui, M. N. 2018. Supply Chain Flexibility in Dynamic Environments: The Enabling Role of Operational Absorptive Capacity and Organisational Learning. International Journal of Operations & Production Management, 38 (3): 636-666 [Emerald]

[26] Sakhri, M. S. A. 2024. Leveraging Digital Data for Optimizing Supply Chain Performance. In H. Nozari (Ed.) Information Logistics for Organizational Empowerment and Effective Supply Chain management. 185-200 [PA, USA: IGI Global]

[27] Sekaran, U. 2003. Research methods for business: A skill building approach. 4th edition [NY: Wiley]

[28] Shekarian, M., Nooraie, S. V. R. and Parast, M. M. 2020. An Examination of the Impact of Flexibility and Agility on Mitigating Supply Chain Disruptions. International Journal of Production Economics, 220: 107438 [Elsevier]

[29] Shukor, A. A. A., Newaz, M. S., Rahman, M. K., Taha, A. Z. 2021. Supply chain integration and its impact on supply chain agility and organizational flexibility in manufacturing firms. International Journal of Emerging Markets, 16 (8): 1721-1744 [Emerald]

[30] Steen, R., Haug, O. J., Patriarca, R. 2023. Business continuity and resilience management: A conceptual framework. Journal of Contingencies and Crisis Management, 32 (e12501): 1-13 [Wiley]

[31] Vaseei, M. 2024. A Conceptual Framework for Blockchain-Based, Intelligent, and Agile Supply Chain. In H. Nozari (Ed.) Information Logistics for Organizational Empowerment and Effective Supply Chain management. 150-162 [PA, USA: IGI Global]