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Factors Related to Modern Capabilities in Logistics Engineering and their Influence on Supply Chain Resilience and Flexibility

Amit Kulkarni[1], Ravindra Pathak[2*]

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Abstract: Industry 4.0 technologies have shaped the logistics capabilities under their new framework of Logistics 4.0. Under the evolving framework of Logistics 4.0, the industrial electrical and mechanical machines traditionally controlled by on-plant supervisory programmable logic controllers can be controlled by software-based monitoring and control systems hosted on cloud computing. This shift towards vertical integration requires all machines and equipment to transmit data from their sensors directly to the cloud-hosted software designed to monitor and control multiple manufacturing plants spread globally. Thus, a fully interconnected system of machines and equipment can be achieved enabling visualization of the physical processes at the cloud computing layers. In this evolution, the traditional ERP and MRP systems can be deployed on cloud computing for controlling multiple manufacturing plants spread globally. Further, layers of intelligent software systems using artificial intelligence and machine learning can be deployed for advanced predictive analytics. In such an environment, new logistics capabilities can be created: digitalization, real time visibility of logistics events, automated remote monitoring and controls, self-configuration and diagnostics, self-collaboration and communication, intelligent management of dynamic processes, and cognitive and environmental awareness. This research investigated their impacts on supply chain resilience and flexibility using the Fuzzy Interpretive Structural Modeling (FISM) method. Rankings of influences were collected from eighteen experts using a five-level scale. The rankings were processed and analyzed using the FISM method. The final model shifted the intelligent management of dynamic processes to the dependent variables' group alongside supply chain resilience and flexibility thus creating a model of the remaining above-mentioned variables grouped as independent variables influencing them. Revisiting theory, it was proposed that digitalization and real time visibility of logistics events are foundations for enabling the remaining new logistics capabilities. Remote monitoring and control of logistics events can be done by cloud-based applications supporting the ERP and CRM. The self-diagnostics capabilities may help the machines in invoking preventive maintenance and troubleshooting thus improving their longevity and reducing their outages. Environmental awareness may help in reducing disruptions, outages, engineering failures, and environmental hazards. The key aspect to be kept in mind is that every plant and other facility networked under the Logistics 4.0 framework should have digitization feasibility of all machines and reliable Internet connection at sufficient capacities.

Keywords: *Logistics 4.0, Logistics Engineering, Digitalisation, Supply Chain Resilience, Supply Chain Flexibility*

1. Introduction

Modern logistics engineering is shaped by new capabilities enabled by Industry 4.0 technologies to enhance delivery effectiveness and efficiency, reduction of losses and damages, reduction of lead times, reduction in stalled inventories, reduction of logistics costs, better flexibility and responsiveness in deliveries, and better risk awareness and mitigation (Bigliardi, Casella, and Bottani, 2021; Woschank and Dallasega, 2021). These new capabilities in modern logistics engineering are driven by several technology-enabled enhancements catering to new process modeling, new data-driven planning and data analysis systems, new smart capabilities in equipment and machinery, automation in transportation and logistics engineering, and sustainability with circular economy capabilities (Dallasega et al., 2022; Jabbour et al., 2018).

Industry 4.0 is primarily linked with integration and digitization of the entire business model of logistics and supply networking (Kucukaltan et al., 2022). The logistics operations enabled by adopting Industry 4.0 technologies are called Logistics 4.0, in which the value chain of physical components is entire digitalized and integrated with digital analytics, command, and control systems preferably running on cloud computing platforms. With the evolution of Logistics 4.0, a complex evolution of interactions between humans and machines is also evident. The machines can collaborate and communicate in groups and also to the command-and-control systems following new communication protocols emerging under a category called "Machine Type Communications (MTC)". Human operators and decision makers do not get directly involved in the MTC

[1]*Research Scholar, Mechanical Engineering Department, Medicaps University Indore, MP, India*
Email: amit.kulkarni@medicaps.ac.in
[2]*Associate Professor, Mechanical Engineering Department, Medicaps University Indore, MP, India*
email: ravindra.pathak@medicaps.ac.in
***Corresponding Author:-** Ravindra Pathak
[2]*Associate Professor, Mechanical Engineering Department, Medicaps University Indore, MP, India*
Email: ravindra.pathak@medicaps.ac.in

albeit are involved in a number of interventions for commanding and controlling the Logistics 4.0 performance. Research studies are required to investigate how these interactions are shaping the processes in logistics and supply networking to build new capabilities driving supply chain performances such as flexibility, agility, resilience, and responsiveness.

Amidst the hype around Industry 4.0 and Logistics 4.0, the average logistics personnel may consider them as adoption of new technologies and hence will value the awareness of their success factors and the chances of their failures (Khan et al., 2022). The core technologies of Industry 4.0 are Industrial Internet of Things (IIoT), short and long-distance communications, Cyber Physical Systems (CPS), Big Data Analytics (BDA), and Machine Learning for Artificial Intelligence (MLAI). Adopting these technologies require changes in business model, smartness of work culture, adoption of new skills and responsibilities, and automation in multiple systems. There are implications related to leadership and management, employment, transformation of existing infrastructure, education and trainings, top management commitment, and new organizational business strategy matching the new logistics capabilities.

This research is designed to investigate the enabling factors related to modern capabilities in Logistics Engineering under Logistics 4.0 and further investigate their influences on two critical supply chain performance attributes: Resilience and Flexibility. The reasons for choosing these two supply chain performance variables are discussed in Section 4.0 of this paper.

The research questions investigated are the following:

(a) What are the key factors and their interrelationships related to modern capabilities in Logistics Engineering?
(b) How these key factors influence Supply Chain Resilience and Flexibility?

The highlights of the research are the following:

(a) A theoretical review of Industry 4.0 and Logistics 4.0, the factors related to modern capabilities in Logistics Engineering, and Supply Chain Resilience and Flexibility;
(b) Ratings on influence of logistics engineering factors on supply chain performance following a survey approach among eighteen logistics engineering specialists working in industrial states of MP and UP in India;
(c) A fuzzy interpretive structural model (FISM) evolving from the logistics engineering specialists showing the key factors and their interrelationships related to modern capabilities in Logistics Engineering and their influence on Supply Chain Resilience and Flexibility;
(d) A detailed recommendation on using the interpretive structural model for future research;

The next three sections present the literature review of the existing theories related to the research topic.

2. Industry 4.0 and Logistics 4.0:

Logistics engineering is an integrated domain of several engineering disciplines to facilitate, monitor and control logistics operations (Bartodziej, 2017; Michlowicz, 2021; Pissardini and Sacomano, 2020; Plinta, 2016). Traditionally, these disciplines have been the electrical, mechanical, and civil engineering, operations research, communications engineering, and information technologies relevant to a common umbrella discipline of industrial engineering. IIoT, CPS, BDA, and MLAI have evolved collectively as new paradigms under the industrial engineering umbrella (Khan et al., 2022; Kucukaltan et al., 2022). Amidst all the new technological evolution and hypes, the fundamental quests of logistics engineering are already defined in literature (Christopher, 2022; Michlowicz, 2021). They are stated as the following:

(a) Minimizing lead times in all processes and transportation;
(b) Ensuring optimum shaping of the logistics networking fitting the business model;
(c) Distributing all the transportation streams in the network to achieve reliable and timely deliveries;
(d) Selecting and positioning the right machines and equipment in the network to achieve optimum operating performance;
(e) Reducing the inventory holding levels and costs;
(f) Efficient management of logistics resources;
(g) Solving conflicts and reducing wastages through logistics and transportation operating curves and applying queuing theory principles;
(h) Accounting and optimisation of in-plant logistics operations following the storage and production operating curves;
(i) Integrating the logistics systems and processes of the supply chain stages to build the horizontal value chain network;
(j) Integrating all engineering components end-to-end in the value chain network catering to the full production life cycle (including the circular economy reverse logistics);
(k) Integrating communications channels across the value chain network;

Industry 4.0 is an evolution of advanced manufacturing and logistics engineering systems capable of better networking among manufacturing partners ensuring better business and operating models driven by trust relationships, information sharing, and transparent communications (Tao *et al.*, 2014, 2014a; Unal *et al.*, 2021; Vermesan *et al.*, 2014; Zhong *et al.*, 2016). IIoT technology is at the core of Industry 4.0 for integrating the physical world with the computing world designed for data analytics, monitoring, and control (Li and Si, 2017). IIoT is used for information flow from the field engineering systems into the core processes comprising production planning and control, scheduling, procurement, manufacturing, inventory control, and delivery to customers (Pissardini and Sacomano, 2020). The primary information flows initiate from the field sensors used for automated information transfer about inventory control, sales and orders, demand capturing points of the product lines, production capacity utilised, supplies already scheduled in channels, forecasting (related to demand loads, deadlines, and expenses), and control efficiency (a measure of costs and deadlines met). The enablers of primary information flows are sensors, IIoTs, CPS, their communication interfaces, software firmware, big data analytics, and intelligent analytics installed on the cloud computing platforms.

IIoTs are Internet of Things designed for industrial applications (Liu et al., 2022). IIoTs can be attached with embedded software in devices to enable localised information processing and communications capabilities in them (Bartodziej, 2017; Carlsson, 2017; Liu et al., 2022). The embedded software is built with Java or JavaScript firmware designed for field operations of the devices. They are capable of integrating physical sensors and activators attached with the devices to form a localised sensor network remotely operated and controlled by the distributed programmable logic controllers (PLC). The PLCs are further integrated using localised industrial computers running plant level scheduling, monitoring and control protocols. These systems have existed during the Industry 3.0 era. In Industry 4.0, introduction of IIoTs and resulting transformation of field devices and PLCs into CPS have enabled new communication capabilities using open protocols such as Advanced Message Queuing Protocol (AMQP), IPv6, and message queuing telemetry transport (MQTT) (Naik, 2017). The new communication capabilities have enabled modern open data transmissions beyond the physical boundaries of manufacturing plants and their logistics facilities thus forming the scope and opportunities for manufacturing and logistics networking.

The new evolved architecture of manufacturing and logistics is driven by real time visualisation of the field events and remote monitoring and control of plants, robotics, and machinery (Bartodziej, 2017; Lim, Xiong, and Wang, 2021; Qu *et al.*, 2016). In Industry 3.0, the remote monitoring and control existed in small, closed domains controlled by distributed PLCs. In Industry 4.0, the monitoring and control capabilities are extended to cloud-based applications (Abdmeziem, Tandjaoui, Romdhani, 2016; Henzel & Herzwurm, 2018; Unal et al., 2021). Cloud based scheduling, monitoring, and control of field manufacturing systems is called “Cloud Manufacturing”, which enables pooling of manufacturing resources and services of several manufacturing partners using cloud-based manufacturing software applications (Ghomi, Rahmani, Qader, 2019; Lim, Xiong, and Wang, 2021; Qu *et al.*, 2016). The layers of cloud manufacturing are presented in Figure 1 (simplified form of Bartodziej, 2017; Lim, Xiong, and Wang, 2021; Qu *et al.*, 2016).

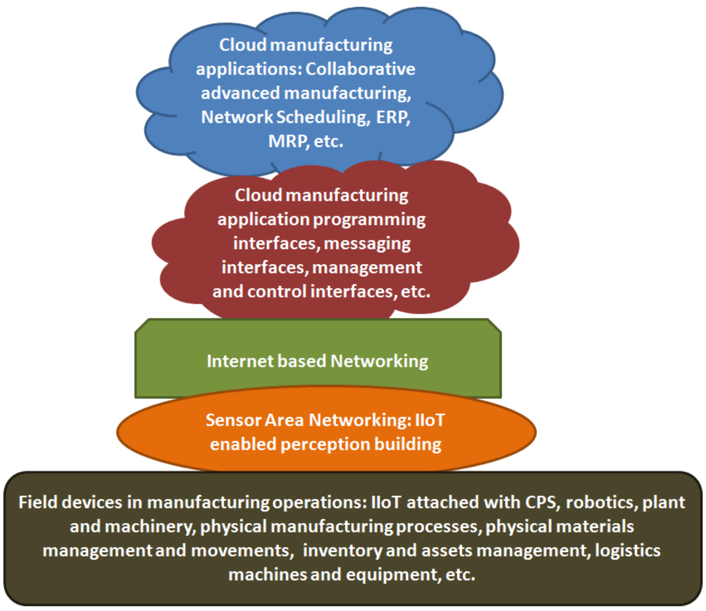

Fig 1: Layers of cloud manufacturing (simplified form of Abdmeziem, Tandjaoui, Romdhani, 2016; Bartodziej, 2017; Lim, Xiong, and Wang, 2021; Qu et al., 2016)

The layers of cloud manufacturing shown in Figure 1 facilitate networking of several manufacturing partners serving common customers (Bartodziej, 2017; Lim, Xiong, and Wang, 2021; Qu *et al.*, 2016). The field devices of several manufacturing plants can be integrated using IIoT and CPS technologies enabling them to contribute to common perception building in a sensor area networking. The common perception data is transmitted to the cloud layers through Internet-enabled networking. The entry points to cloud manufacturing applications are facilitated by application programming interfacing, messaging interfacing, and interfaces for management and administration. Overall, this is quite complex system. The incentives for adopting this architecture depend upon the modern logistics capabilities achieved by business owners. Hence, the factors enabling these capabilities determine the success of Industry 4.0 and Logistics 4.0. The next section presents a review in this context.

3. Factors related to modern logistics capabilities under Logistics 4.0:

The field-level manufacturing and logistics systems of several manufacturers forming a common perception layer enables synchronisation of the CPS devices enabling what is known as smart capabilities (Qu *et al.*, 2016). The smart CPS devices are capable of real-time data collection and transmission to data analytics, monitoring, and control software systems on cloud computing. In a near field communications network, the smart CPS devices can collaborate and communicate mutually in a framework of edge computing. They can actively interact with the environment where they are operating (as either static or mobile devices). The locations of the CPS devices can be tracked using location-based positioning and traceability services embedded within the edge computing framework (Zhang *et al.*, 2017). The positioning system can be operated using interactive maps and augmented reality overlapped with big data as an integrated software system (Krstic, Tadic, and Zecevic, 2021).

There are several applications of smart capabilities in Logistics 4.0. The data collected from sensors are transmitted to manufacturing and logistics analytics services almost in real time thus enabling real time forecasting analysis by applying time series and regression analysis statistics. Smart capabilities also help in efficient field operations, cognitive awareness of CPS devices, optimised scheduling, reduced queuing and waiting times, advanced tracking and tracing of assets, resources and products, controlling the operations through augmented reality, and controlling the "value addition" of the value-added services (Cimini *et al.*, 2020; Krstic, Tadic, and Zecevic, 2021; Qu *et al.*, 2016; Unal et al., 2021; Zhang *et al.*, 2017).

A vertical integration between the field devices (and their combined perception layer) and the higher layers in the cloud manufacturing interfaces and applications is facilitated by long distance broadband communications networking using 5G LTE or urban Wi-Fi technologies (Lim, Xiong, and Wang, 2021; Wollschlaeger, Sauter, and Jasperneite, 2017). By term "vertical integration" it is implied that all the electrical and mechanical systems deployed in the production areas, which can be controlled through programmable logic are controlled remotely using digital technologies and data communications deployed higher in the system hierarchy, preferably on the cloud computing. The monitoring and controlling operations from centralised cloud manufacturing systems are facilitated from the cloud-based manufacturing and logistics controllers. These controllers receive data streams from the sensor groups, which are registered in a centralised repository of sensors. The sensory data helps in building real time perception of the field operations. The operations are remotely controlled by issuing actuation commands by the cloud controllers. The low-level physical actions by machines, robots, vehicles, equipment, etc. can be commanded by remote actuation controllers. This entire framework operates under automated control systems running on the cloud manufacturing system. A reliable and efficient industrial communication system is a major factor for making remote monitoring and control of field operations successful. Industrial communication has evolved from a variety of proprietary protocols and links to the modern IPv6, LTE, MQTT, AMQP, and other open standards protocols and links.

As described by Li and Si (2017: 609), an intelligent manufacturing system designed with Industry 4.0 technologies comprises of several modernised dynamic capabilities in the domains of multi-time-scale dynamic processes, space-time dynamic processes, and multi-level hybrid dynamic processes. These dynamic processes were very difficult operate without the Industry 4.0 technologies. A manufacturing organisation can quickly scale up or down operations and also modify production and supplies as per the demand patterns rapidly. Significant uncertainties exist in these processes requiring development of capabilities to manage uncertainties and complexities. Several layers of control structures are required at supervisory level, logic level, and at the process loop level. The entire system is required to be self-configurable, which requires loose connections, soft rules, and smart decision-logic capable of making events-driven decisions. They are partially human controlled and partially controlled by MLAI.

Summarising the above, the key factors related to modern capabilities in logistics engineering are digitalisation for vertical integration, real time visibility of logistics events, automated remote monitoring and controls, self-configuration and diagnostics, self-collaboration and communication, cognitive and environmental awareness, and intelligent management of dynamic processes. This research aims to study the influence of these variables on supply chain resilience and flexibility. Before starting the primary research, a review of supply chain resilience and flexibility is presented in the next section.

4. Supply chain resilience and flexibility:

To understand the contexts of supply chain resilience and flexibility, the modern evolution of supply chain needs to be understood. In the modern world of globalisation and liberalisation, supply chains were interconnected globally transforming them into supply chain networks (Christopher, 2018). Global connections offered several advantages to the manufacturing companies and supply chain networks operators, such as lean and just-in-time practices. However, global connections also raised the level of interdependencies among the supply network nodes and routes. There is high probability that failures at certain nodes in the network of supply chains can propagate their knock-off effects to other parts. Hence, the canvas for risk management in modern supply chain networks has expanded significantly. There can be several sources of risks in supply, demands, process, control, environment, and geopolitics contexts.

To build supply chain resilience against the globally dispersed risks, they need to adopt cultural, process, and capability maturity of risk management (Kumar and Anbanandam, 2020; Li et al., 2020; Roque Jr., Frederico, and Costa, 2023). Technology excellence, supply chain integration, information sharing, flexible manufacturing strategies, commercial flexibility, supply flexibility, partnership flexibility, inventory flexibility, market/demand related flexibilities, and absorbing, restorative, and adaptive capacities are key capabilities determining supply chain resilience. In fact, flexibility in several supply chain management domains is required to achieve supply chain resilience.

Flexibility in supply chains can be achieved by continuously looking into, studying, and analysing their dynamics and making choices about opportunities carefully (Shekarian, Nooraie, and Parast, 2020). Simply stated, it requires intelligent management of dynamic processes in such a way that the organisational exposure to risks of supply disruptions can be controlled based on the organisational business choices and interests. The trade-offs between risk taking and benefits to the organisations need to be estimated carefully such that the cost of accepting or mitigating risks is budgeted in the opportunities availed. This capability is the supply chain flexibility, which can be achieved in tandem with agility (Irfan, Wang, and Akhtar, 2020). Agility is about quick decision-making about the actions after analysing the information collected about a situation, and flexibility is about taking actions based on situation. Agility requires information integration to make decisions about operating the flexibility available to an organisation in a given situation and flexibility requires integration of supply chain echelons and their processes to build dynamic capabilities to respond to the situations it faces (Irfan, Wang, and Akhtar, 2020; Shukor et al., 2021). An integrated and intelligent management system for information and supply chain process integration is essential to generate and operate both agility and flexibility. Such a management system can strengthen organisational resilience against supply chain disruptions. Recent studies indicate the role of Industry 4.0 technologies as enablers of flexibility and agility, and in building strong organisational resilience (Fatorachian and Kazemi, 2021; Ghadge et al. 2020; Ralston and Blackhurst, 2020; Shukor et al., 2021). As this research is about factors related to modern capabilities in logistics engineering and their influence on supply chain resilience and flexibility, the role of Industry 4.0 is vital. As reviewed earlier in this research, the specific Logistics 4.0 capabilities have evolved from the foundation of Industry 4.0.

A methodology to investigate a multivariate model for investigating the influence of modern logistics capabilities on supply chain resilience and flexibility is presented in the next section.

5. Research Methodology:

The research methodology followed in this research is quantitative with induction logic following interpretive philosophical approach (Saunders, Lewis, and Thornhill, 2009). This design helps in evolution of new theories and models related to the phenomena under study. The method selected for this research is fuzzy interpretive structural modelling (FISM), which helps in deriving a relational matrix with the help of experts. The experts selected were eighteen logistics engineering specialists working in industrial states of MP and UP in India. The researcher approached twenty-eight experts and could get completed responses from eighteen out of them. The profiles of the respondents who sent completed responses are the following:

Respondents 1 to 11: Engineers working on digitalised manufacturing processes operating the equipment communicating to centralised monitoring and control systems hosted within the plants through local open standards networking and five of them having on Internet;

Respondents 12 to 16: Technical supervisors operating entire shop floors of digitalised manufacturing processes; one of these four has been operating an entire plant;

Respondents 17 and 18: Owners of digitalised manufacturing plants getting their production orders from a network application for order bookings and payments operated over the Internet;

This research followed the survey method for interacting with the experts and collecting data from them (Yin, 2011). As described by Yin (2011), surveys result in constrained responses restrained by the allowed degrees of freedom in a structured questionnaire. Hence, responses collected from surveys are measurable. The steps followed for this method are the following (as explained by Das, Azmi, and James, 2020; Hunie, 2022; Tyagi, Sharma, and Shukla, 2019):

(a) The first step was to identify the variables to be discussed with the experts. In this research, the variables are the factors related to modern capabilities in logistics engineering and supply chain resilience and flexibility;

(b) The second step was to organise these variables in a Structural Self-Interaction Matrix (SSIM). This matrix comprises the variables entered as row as well as column headers in such a way that all pairs of combinations can be formed within the matrix. The variables in the row headers are designated as "i" and the ones in the column headers are designated as "j". The "i" variables are indicated as influencers indicated in the leftmost column, and the same variables are indicated as influenced (repeating the same sequence of the stated column) as "j" variables.

(c) The third step was to decide a nature of relationship between the variables in each of the pairs defined. The relationships are defined as V (the factor "i" has an influence on factor "j"), A (the factor "j" has an influence on factor "i"), X (both factors "i" and "j" have mutual two-way relationships), and O (there is no relationship between factors "i" and "j"). The relationships may have varying strengths in either direction depending upon their known theoretical implications. The design of the SSIM ensures that the nature of every variable as an influencer and as the influenced can be showed. The SSIM is a M X M matrix in which, every variable influencing every other variable within a group of variables can be shown following one-to-one relationships in both directions of all the variables in the group. At the diagonal line of the SSIM matrix, the self-influences of the variables are shown as "1".

(d) The next step in fuzzy ISM was to record the strengths of relationships in V, A, and X. At fundamental level, four main levels are defined in the scale: perfect influence (P), strong influence (S), moderate influence (M), weak influence (W), and no influence (N). A sixth level called absolute influence is also entered as "1" representing a factor influencing itself. Thus, the total number of levels in the fundamental scale is five. The terms V, A, X, O, P, S, M, W, and N are called linguistic terms. There is no hard rule for defining linguistic terms. Every researcher is free to choose what best suits the study. The number of levels can be increased if required by the objectives of a research. This study has adopted the fundamental structure of five levels as shown in the Table 1. The highest level is the Level 5 indicating perfect influence, and the lowest level is the Level 1 indicating no influence. The fuzzy values of the five levels are presented as the following (Tyagi, Sharma, and Shukla, 2019):

Table 1: Five level scale with fuzzy values for each level

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

The three numbers in brackets indicate that the fuzzy numbers are triangular. Figure 2 and Equation (1) below show the triangular fuzzy number $\mu_A(X)$ represented as (Elizabeth and Sujatha, 2014):

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

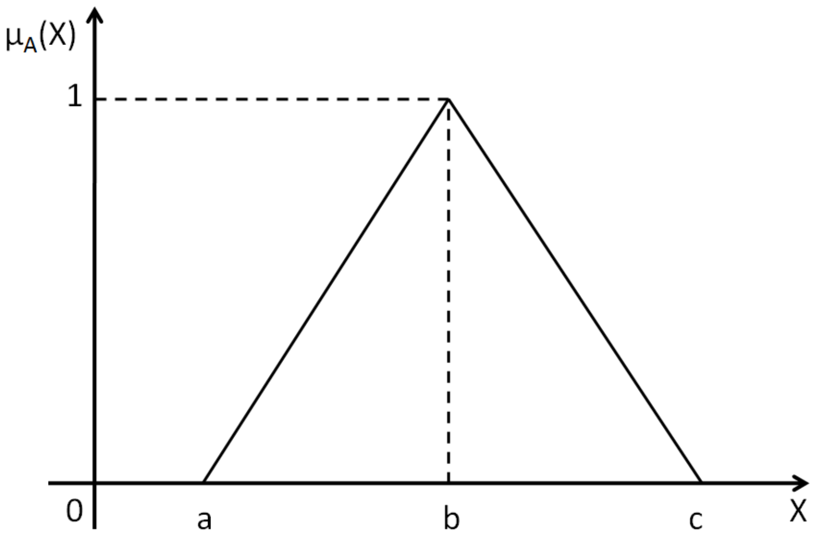

Fig 2: Triangular fuzzy number

(e) The next step was to enter the values in the SSIM using linguistic equivalents of relationships as well as their fuzzy values. These are the values collected from each expert proving their respective SSIM matrices. This research approached 28 experts and received responses from eighteen out of them. Here, the relationships V and A can have three values each represented linguistically as V (S), A (S), V (M), A (M), V (W), and A (W) (Das, Azmi, and James, 2020). Given that X represents bidirectional relationships, it can have nine values: X (S, S), X (S, M), X (S, W), X (M, S), X (M, M), X (M, W), X (W, S), X (W, M), and X (W, W). The relationship O can have only one value O (N). Each respondent provided their respective SSIM tables using these symbols.

(f) The next step was to transform the SSIM by converting linguistic equivalents to defuzzified values. Defuzzification of triangular fuzzy numbers can be carried out using multiple methods. This research selected the method of magnitude measure using the following formula (Elizabeth and Sujatha, 2013, 2014):

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

Using the formula for magnitude of the triangular fuzzy number, the defuzzified number is tabulated in Table 2:

Table 2: Five level scale with triangular fuzzy values and defuzzified values using magnitude method for each level (Elizabeth and Sujatha, 2013, 2014):

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

(g) The next step is to combine the data of all the responses to arrive at the aggregated defuzzified SSIM table. The responses were collected in SSIM formats using linguistic terms defined in the Step (e), which were converted to fuzzy numbers and then were triangulated using the magnitude method for defuzzification. After achieving the magnitude numbers, the responses of the eighteen respondents were combined using MODE method, which captures the values having highest frequencies in the responses (Das, Azmi, and James, 2020; Jain and Soni, 2019; Khatwani et al., 2014; Mohanty and Shankar, 2017).

(h) The next step was to create the reachability matrix. The reachability matrix simply shows the relationships, which can be shown as “1”. After defuzzification and aggregation, only the relationships P (perfect), S (strong), and bidirectional relationships with at least one direction having P or S have been retained and others dropped out of the SSIM. In the initial reachability matrix, only the direct relationships are shown. To show all possible relationships, a final reachability matrix needs to be created in which, every direct and indirect relationships are explored and shown. This table can be formed after checking all the transitivity relationships and filling the missing gaps. The final reachability matrix sets a precedent for the next table called the level partitioning table explained in step (i).

(i) The next step was to conduct the MICMAC (Matrix Impact-Cross Multiplication Applied to Classification). It is a four-quadrant plotting of the variables as per their driving and dependence powers. The four quadrants are: autonomous, dependent, independent, and linkage.

(j) Level partitioning table was the next step in which, the reachability, antecedents, and intersections are presented.

(k) The next step was to show the conical matrix showing the driver and dependence powers numerically.

(l) The next step was to produce the diagram showing all the relationships in the form of a path diagram.

(m) Finally, the FISM model was drawn pictorially representing an output of this research. This model was discussed theoretically by finding reflections of the theoretical understanding formed in literature review.

It may be noted that FISM presents the collective validated opinions of experts of the subject matter under study, which cannot be treated as established because the results are expected to vary slightly in repeated studies in different individuals. Hence, this research is about exploring theoretical relationships using interpretive approach but not confirming them as is possible in the deductive approach. FISM is not a substitute of advanced multivariate quantitative methods that are known to produce empirically established results. For deriving such outcomes, a large group of experts should be sampled and the multivariate analytical methods such as multiple regression, MANOVA, or structural equation modelling should be conducted. The discussion on results of this research is presented in the next section.

6. Results and Discussion:

In this section the final results of FISM method following the steps explained in the previous section are produced and discussed. The Table 3 shows all the factors derived from the literature review. As mentioned in the research objectives, the interrelationships among all the driving factors F1 to F9 were studied through FISM.

Table 3: Variables derived from literature review

Factors	Names
F1	digitalization for vertical integration
F2	real time visibility of logistics events
F3	automated remote monitoring and controls
F4	self-configuration and diagnostics
F5	self-collaboration and communication
F6	cognitive and environmental awareness
F7	intelligent management of dynamic processes
F8	supply chain resilience
F9	supply chain flexibility

These factors were shared with the experts team comprising of twenty-eight logistics engineering specialists working in industrial states of MP and UP in India. Out of them, eighteen responded. The profiles of the respondents are presented in the previous section. Their first task assigned was to allocate all relationships a code out of X (S, S), X (S, M), X (S, W), X (M, S), X (M, M), X (M, W), X (W, S), X (W, M), X (W, W), V (S), V (M), V (W), A (S), A (M), and A (W) and O (N) in the SSIM template shared with them. The meanings of these codes are described in Point (c) of Section 5. The eighteen responses were entered in an Excel sheet in separate tabs. In each of these tabs, the SSIM matrices with fuzzified and defuzzified values were entered based on their individual responses. Finally, the mode values (highest frequencies of the defuzzified values) of all eighteen responses were entered in the finalized aggregated SSIM matrix. The finalized SSIM showing the aggregate (mode) values of the defuzzified values is presented in Table 4 below:

Table 4: Aggregate (mode) values of the defuzzified values entered in the finalised SSIM

Variables	F1	F2	F3	F4	F5	F6	F7	F8	F9
F1	1	0.5625	0.375	0.5625	0.729	0.375	0.729	0.729	0.729
F2	0.375	1	0.375	0.0208	0.0208	0.375	0.729	0.375	0.375
F3	0.729	0.0208	1	0.375	0.375	0.375	0.1875	0.375	0.375
F4	0.729	0.0208	0.0208	1	0.375	0.375	0.0208	0.375	0.375
F5	0.729	0.0208	0.0208	0.375	1	0.375	0.375	0.375	0.375
F6	0.0208	0.0208	0.0208	0.5625	0.375	1	0.375	0.375	0.375
F7	0.0208	0.0208	0.0208	0.0208	0.375	0.375	1	0.375	0.375
F8	0.0208	0.0208	0.0208	0.0208	0.0208	0.0208	0.0208	1	0.375
F9	0.0208	0.0208	0.0208	0.0208	0.0208	0.0208	0.0208	0.0208	1

The Table 4 indicates existence of perfect relationship (P = 0.729), strong relationship (S = 0.5625), moderate relationships (M = 0.375), weak relationships (W = 0.1875), and no relationships (N = 0.0208) between the pair of variables shown in the SSIM. The finalised SSIM with corresponding fuzzy values is shown in Table 5.

Table 5: SSIM with Fuzzy values

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

The linguistic equivalents of each relationship were also entered in a separate table, as shown in Table 6. In the subsequent analysis, the relationships V (M), V (W) and O (N) were dropped. The relationships X (S, S), X (S, M), X (M, S), V(P), and V (S) were retained for further analysis. The Internet tool by Ahmad and Ayman (2021) was used to generate the reachability matrix. The X (M, M), V (M), V (W) and O (N) were treated as "O" in subsequent steps.

Table 6: SSIM with Linguistic Equivalents

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

Now the picture is clear. There were four forward perfect relationships, ten bidirectional relationships (five with at least P and S in one direction), one weak relationship, two no relationships, and the remaining were moderate relationships. The relationships were entered in the Internet-enabled tool by Ahmad and Ayman (2021) as shown in the Figure 3 below. The X (S, S), X (S, M), and X (M, S) values are indicated as X and the V (P) and V(S) values are indicated as V. The X (M, M), V (M), V (W) and O (N) values are treated as O. The experts provided their opinions on not only existence or absence of relationships but also about the strengths of relationships. To adjust the relationships for validity, only the perfect and strong relationships have been retained. In bidirectional relationships, the ones having at least P or S in one of the directions have been retained with a perception that such relationships may have some value in their contribution to the overall model. In theory, every relationship may have some importance in the bigger picture. The model comprising of moderate relationships may be much more expanded and complex. However, the model with moderate relationships may not produce a realistic theoretical construct. The focus needs to be on the most influential relationships in the model. Hence, only the P and S relationships may carry value in defining the specifications of the bigger picture. Other relationships may be studied by an interested researcher as a by-product of the main theoretical construct.

SmartISM: Smart Interpretive Structural Modeling

	F1:digitalisation for vertical integration	F2:real time visibility of logistics events	F3:automated remote monitoring and controls	F4:self configuration and diagnostics	F5:self collaboration and communication	F6:cognitive and environmental awareness	F7:intelligent management of dynamic processes	F8:supply chain resilience	F9:supply chain flexibility
F1:digitalisation for vertical integration		X	X	X	X	O	V	V	V
F2:real time visibility of logistics events			X	O	O	O	V	O	O
F3:automated remote monitoring and controls				O	O	O	O	O	O
F4:self configuration and diagnostics					O	X	O	O	O
F5:self collaboration and communication						O	O	O	O
F6:cognitive and environmental awareness							O	O	O
F7:intelligent management of dynamic processes								O	O
F8:supply chain resilience									O
F9:supply chain flexibility									

Calculate ISM Results

Fig 3: SSIM of only X (S, S), X (S, M), X (M, S), and V (S) values retained in the aggregated (mode) values of defuzzified triangulated values

The Figure 3 shows the screenshot when the SSIM was populated with the essential relationships as defined. On pressing the "Calculate ISM Results" button, the rest of the reports were generated. In the next step, the initial reachability matrix was formed. This matrix requires that all selected relationships for further analysis are shown as "1". The rejected relationships because of fuzzy analysis have not been included in this matrix. The initial reachability matrix was formed as shown in Table 7 using the Smart ISM application by Ahmed and Ayman (2021).

Table 7: Initial Reachability Matrix created in Smart ISM application by Ahmed and Ayman (2021)

Reachability Matrix(RM)

Variables	1	2	3	4	5	6	7	8	9	Driving Power
F1:digitalisation for vertical integration	1	1	1	1	1	0	1	1	1	8
F2:real time visibility of logistics events	1	1	1	0	0	0	1	0	0	4
F3:automated remote monitoring and controls	1	1	1	0	0	0	0	0	0	3
F4:self configuration and diagnostics	1	0	0	1	0	1	0	0	0	3
F5:self collaboration and communication	1	0	0	0	1	0	0	0	0	2
F6:cognitive and environmental awareness	0	0	0	1	0	1	0	0	0	2
F7:intelligent management of dynamic processes	0	0	0	0	0	0	1	0	0	1
F8:supply chain resilience	0	0	0	0	0	0	0	1	0	1
F9:supply chain flexibility	0	0	0	0	0	0	0	0	1	1
Dependence Power	5	3	3	3	2	2	3	2	2	

As described in Step (h) of Section 5, the initial reachability matrix comprises of only the direct relationships. The driving and dependence powers are also shown in Table 7. The root of driving power is with F1 whereas the F7, F8, and F9 are the factors with most dependence power. This is explained theoretically after the finalised model. The final reachability matrix is shown in Table 8. As discussed in Point (h) of Section 5, the final reachability matrix comprises of all the direct and indirect relationships. It may be noted that the driving and dependence powers have changed when all the indirect relationships are accounted for. Now, F1 to F6 are shown with equal driving powers whereas F7 to F9 retain their dependence status. The Table 8 shows the complete matrix of dependencies. The numbers with stars indicate that only indirect relationships exist between those variables.

Table 8: Final Reachability Matrix created in Smart ISM application by Ahmed and Ayman (2021)

Final Reachability Matrix(FRM)

Variables	1	2	3	4	5	6	7	8	9	Driving Power
F1:digitalisation for vertical integration	1	1	1	1	1	1*	1	1	1	9
F2:real time visibility of logistics events	1	1	1	1*	1*	1*	1	1*	1*	9
F3:automated remote monitoring and controls	1	1	1	1*	1*	1*	1*	1*	1*	9
F4:self configuration and diagnostics	1	1*	1*	1	1*	1	1*	1*	1*	9
F5:self collaboration and communication	1	1*	1*	1*	1	1*	1*	1*	1*	9
F6:cognitive and environmental awareness	1*	1*	1*	1	1*	1	1*	1*	1*	9
F7:intelligent management of dynamic processes	0	0	0	0	0	0	1	0	0	1
F8:supply chain resilience	0	0	0	0	0	0	0	1	0	1
F9:supply chain flexibility	0	0	0	0	0	0	0	0	1	1
Dependence Power	6	6	6	6	6	6	7	7	7	

The driving and dependence powers can also be shown in the MICMAC analysis chart as shown in Figure 4. The MICMAC analysis shows the variables F1 to F6 as the main driving variables with equal powers and F7 to F9 as the dependent variables. There is an interesting observation in the MICMAC analysis. The variables F1 and F6 have a driving power of 9 but also have dependence power of 6. This shows the reachability extent to these variables making them dependent on their predecessors in the initial and final reachability matrices. However, the driving powers of F7 to F9 are merely at unity. Thus, for testing a valid construct, it is logical to consider the variables F1 to F6 as independent variables and the variables F7 to F9 as the dependent variables. Such a construct may be considered as the outcome of this FISM research and used for theoretical interpretations and analysis.

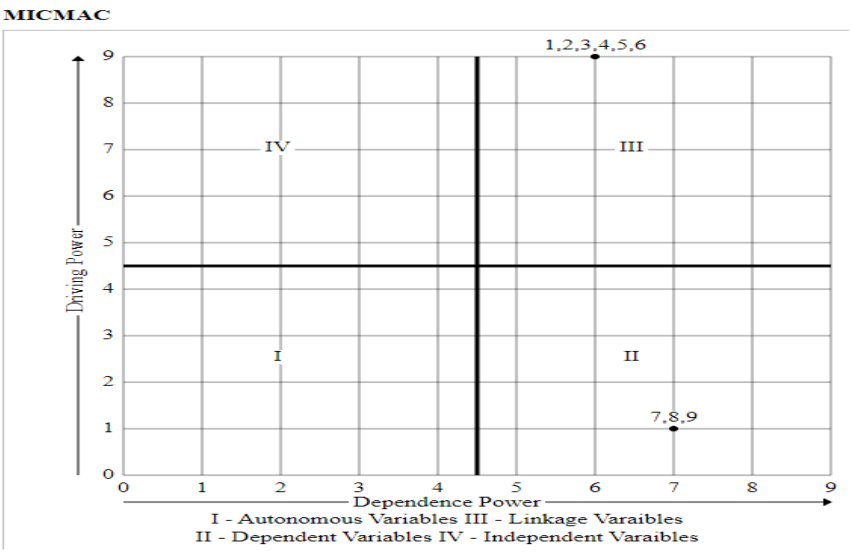

Fig 4: MICMAC chart created in Smart ISM application by Ahmed and Ayman (2021)

The next step was to generate the level partitioning table. The Table 9 shows the sets of antecedents, intersections, and reachability at two levels of partitioning. The partitions represent the chains of relationships when traced individually in the final traceability matrix. This forms a hierarchical structure of the relationships among variables traced. The result shows the independent variable at a higher level (Level 2) than the dependent variables (at Level 1).

Table 9: Level Partitioning Matrix created in Smart ISM application by Ahmed and Ayman (2021)

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, 6,	1, 2, 3, 4, 5, 6,	1, 2, 3, 4, 5, 6,	2
2	1, 2, 3, 4, 5, 6,	1, 2, 3, 4, 5, 6,	1, 2, 3, 4, 5, 6,	2
3	1, 2, 3, 4, 5, 6,	1, 2, 3, 4, 5, 6,	1, 2, 3, 4, 5, 6,	2
4	1, 2, 3, 4, 5, 6,	1, 2, 3, 4, 5, 6,	1, 2, 3, 4, 5, 6,	2
5	1, 2, 3, 4, 5, 6,	1, 2, 3, 4, 5, 6,	1, 2, 3, 4, 5, 6,	2
6	1, 2, 3, 4, 5, 6,	1, 2, 3, 4, 5, 6,	1, 2, 3, 4, 5, 6,	2
7	7,	1, 2, 3, 4, 5, 6, 7,	7,	1
8	8,	1, 2, 3, 4, 5, 6, 8,	8,	1
9	9,	1, 2, 3, 4, 5, 6, 9,	9,	1

Table 10: Conical Matrix created in Smart ISM application by Ahmed and Ayman (2021)

Conical Matrix(CM)

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

Finally, the Table 10 shows the final representation of the full picture in the Conical Matrix. This matrix summarises the finalised reachability, the driving and dependence powers, and the levels of the variables in a single table. This matrix may be viewed as the summary of all the outcomes of the FISM steps conducted in this research. The full reachability can be shown graphically in the form of diagraph shown in Figure 5. While it shows the full scope of inter-relationships and reachability, it represents a very complex picture to be discussed theoretically. Hence, the researcher needs to drop the secondary relationships and even some primary ones to make the research simpler and focussed. For this reason, a finalised model has been created following the power structure of driving and dependence powers and the relationships segregated between the two levels. The relationships within the levels may be dropped. With this approach in mind, the finalised model may be derived as shown in the Figure 6.

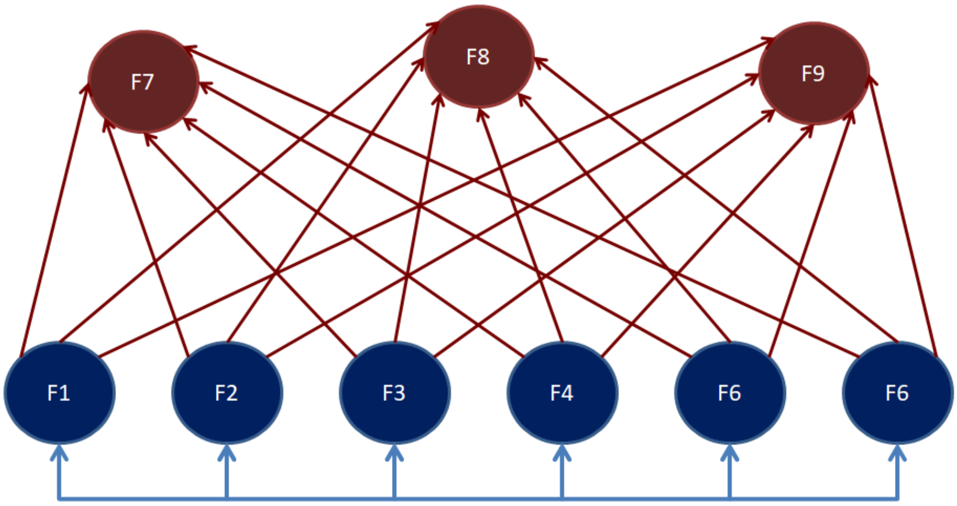

Fig 5: Diagraph chart created in Smart ISM application by Ahmed and Ayman (2021) [redrawn in colour]

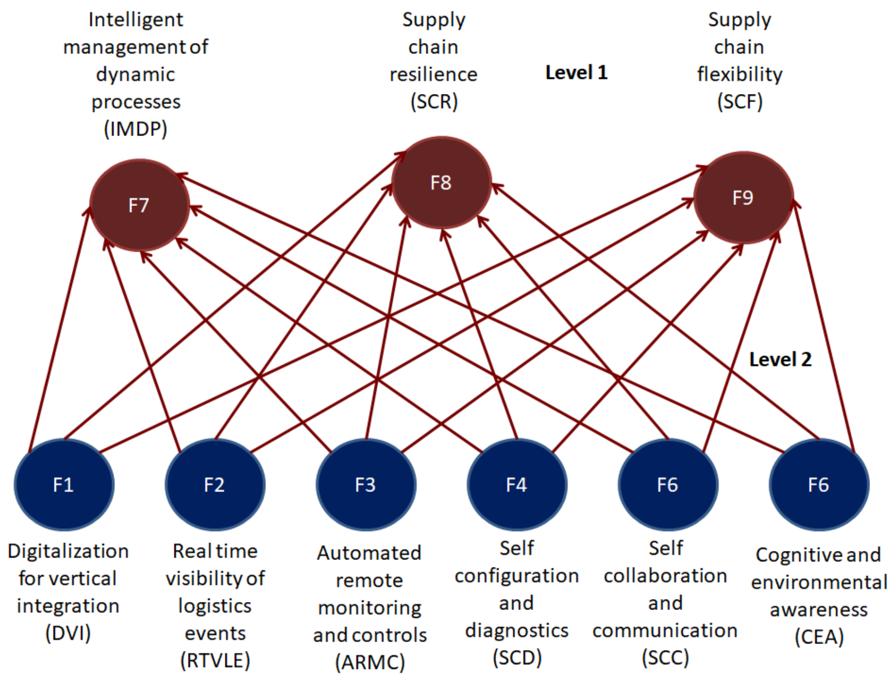

Fig 6: Final Model created in Smart ISM application by Ahmed and Ayman (2021) [Redrawn in colour]

Referring Figure 6, a model showing multivariate relationships between DVI, RTVLE, ARMC, SCD, SCC, and CEA grouped as independent variables, and IMDP, SCR, and SCF grouped as dependent variables. The interrelationships within these groups are ignored to keep the analysis simple and focussed. The variables DVI and RTVLE are foundations required for modern logistics capabilities represented by the other individual factor variables. DVI is a new capability achievable through digitalisation of the electrical and mechanical machines, equipment, and robotics. In the Industry 3.0, they were integrated horizontally using in-plant logic controllers. In Industry 4.0, the controllers are moved to cloud computing thus invoking the capability of managing multiple manufacturing plants through digitalisation and automation. The integration in the Industry 4.0 is thus vertical. The RTVLE is enabled when all the electrical and mechanical machines, equipment, and robotics are digitalised and connected to controllers on cloud computing. They are digitally transformed to send continuous data streams to the cloud-hosted controllers thus forming the required and continuously changing information base for a continuous real time perception or visualisation of the process events executed by them (Li and Si, 2017). The process of such digital transformation involves embedded software built with Java or JavaScript firmware designed for field operations of the PLC devices (Bartodziej, 2017; Carlsson, 2017; Liu et al., 2022). The embedded software helps in digitising the information collected from the sensors reading the running physical process parameters (such as, temperature, flow, revolutions per minute, electrical flux, torque, etc.). With the DVI and RTVLE implemented effectively, the other four Logistics 4.0 capabilities ARMC, SCD, SCC, and CEA can be implemented by virtue of big data systems, applications, and artificial intelligence (Pissardini and Sacomano, 2020). SCD, SCC, and CEA require both cloud and edge computing and communication systems and deployment of MLAI capabilities (Li and Si, 2017).

The logistics capabilities of ARMC, SCD, SCC, and SEA requires deployment of cloud-based applications having the full view of the ground-level running processes via DVI for real-time flexibility and responses (Abdmeziem, Tandjaoui, Romdhani, 2016; Henzel & Herzwurm, 2018; Unal et al., 2021). The Figure 1 presented earlier (drawn based on the concepts explained by Abdmeziem, Tandjaoui, Romdhani, 2016; Bartodziej, 2017; Lim, Xiong, and Wang, 2021; Qu et al., 2016) shows the two cloud layers and the applications to be deployed. In Industry 3.0 systems, the same applications were deployed locally in manufacturing plants having visibility into the processes running in them. On cloud computing, they can visualise processes across multiple manufacturing plants irrespective of where they are located globally. Internet becomes the core medium for communications for this enhancement. New business and operating models have evolved for operating logistics operations, as defined in the literature by some of the latest studies (Christopher, 2022; Khan et al., 2022; Kucukaltan et al., 2022; Michlowicz, 2021). The fundamental quests for logistics engineering presented in Section 2 remain relevant albeit with enhanced performances and new capabilities induced through digitalisation. For example, the ARMC capability may be able to reduce lead times and response times to changes in processes, and the SCD and SCC capabilities may be able to improve on longevity and breakdown periods of all machines and equipment by preventive maintenance and fault elimination. The CEA capability may reduce disruptions, outages, engineering failures, and environmental hazards. The effectiveness of these capabilities may, however, vary by experience, as reflected in the varying rankings provided by the experts. For example, a manufacturing plant or a logistics facility may not achieve feasibility of complete digital transformation because of certain challenges like old machines, poor Internet connectivity, and poor mobile coverage. With such restrictions manual and automated operations may have to be executed in tandem. Such a plant cannot operate a cloud-based monitoring and control software and cloud-based ERP and MRP systems effectively.

As the scope of this research has been completed, a conclusion is presented in the next section.

7. Conclusion:

This research was planned to investigate the key capabilities in Logistics 4.0 for enhancing logistics performance with digitalisation and data-enabled monitoring and control of assets and processes. The research started with a theoretical review of Industry 4.0 technologies and the related Logistics 4.0 capabilities. The key factors of Logistics 4.0 capabilities were derived from this literature review and their influences on supply chain resilience and flexibility were rated by eighteen logistics engineering specialists in the industrial states of MP and UP in India. A survey method was followed allowing the experts to rate the influence of each variable on supply chain resilience and flexibility at five levels. Their ratings were used to follow the Fuzzy Interpretive Structural Modelling method to arrive at a final model. The final model showed the variables digitalization for vertical integration, real time visibility of logistics events, automated remote monitoring and controls, self-configuration and diagnostics, self-collaboration and communication, and cognitive and environmental awareness as modern logistics engineering factors influencing supply chain resilience and flexibility, and intelligent management of logistics processes in logistics engineering domain in a multivariate construct. Mapping with theory, digitalization for vertical integration and real time visibility of logistics events were considered as the foundation and all the other variables using them and activated through cloud-based logistics applications. Without getting into technical details, this research argued with the help of literature review and the expert ratings that the core of modern logistics capabilities is real-time data-driven and transparent perception building about the running physical assets and their processes. If this core is established, the fundamental quests of logistics engineering listed in Section 2 can be achieved. The influence on supply chain resilience and flexibility may be achieved because of real-time visibility into the process events thus reducing decision-making and action times. The new capabilities may be effective in improving supply chain performance in resilience and flexibility albeit with varying effectiveness. For example, automated monitoring and control may reduce process lead times and rapid response times. Further, self-diagnostics may reduce downtimes of machines as maintenance and troubleshooting can be done timely and at times proactively. These improvements can enhance supply chain resilience and responsiveness. However, the solution of digitalisation and cloud-hosted logistics applications may not be suitable for manufacturing plants and logistics facilities having old machines and poor connectivity to the Internet. There may be several old machines with poor digitalisation feasibility. Further, some remote industrial areas may not have good Internet connectivity for running cloud applications.

The future research may be conducted on how Industry 4.0 technologies can influence supply chain resilience and flexibility. Logistics 4.0 is influenced by Industry 4.0 technologies. The future researchers may like to delve deeper into the technical side of Industry 4.0 to investigate how investments made in them can enhance supply chain performances. Industry 4.0 comprises of several generic technologies beyond logistics and manufacturing sectors. In future studies the FISM method may be executed with the help of technical experts of Industry 4.0 technologies, especially in the IIoT and cloud computing domains. Further, the role of Industry 5.0 capabilities in enhancing supply chain performance should also be studied. Industry 5.0 may still be at a hype stage, but several new studies indicate the need for serious research on Industry 5.0 technologies for enhancing logistics and supply chain performances.

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